

- Davidson, James E.H., David B. Stephenson and Alemtsehai A. Turasie (2015) Time series modeling of paleoclimate data *Environmetrics* 27(1) [[HYPERLINK "https://onlinelibrary.wiley.com/doi/abs/10.1002/env.2373"](https://onlinelibrary.wiley.com/doi/abs/10.1002/env.2373)]
- Dergiades, T., R.K. Kaufmann and T. Panagiotidis (2016). Long-run changes in radiative forcing and surface temperature: The effect of human activity over the last five centuries. *Journal of Environmental Economics and Management* 76:67–85. [[HYPERLINK "https://www.sciencedirect.com/science/article/abs/pii/S0095069615000911"](https://www.sciencedirect.com/science/article/abs/pii/S0095069615000911)]
- England, Mark, Lorenzo M Polvani, James A Screen, et al (2025). Surprising, but not unexpected, multi-decadal pause in Arctic sea ice loss. *ESS Open Archive*. March 29, 2025.
- Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. [[HYPERLINK "https://blogs.oregonstate.edu/occri/oregon-climate-assessments"](https://blogs.oregonstate.edu/occri/oregon-climate-assessments)]
- Frajka-Williams, E, C Beaulieu, Aurelie Duchez (2017) Emerging negative Atlantic Multidecadal Oscillation index in spite of warm subtropics. *Scientific Reports*, 7:11224
- Goessling, Helge F. Thomas Rackow and Thomas Jung (2024) Recent global temperature surge intensified by record-low planetary albedo. *Science* Vol 387, Issue 6729 pp. 68-73 [[HYPERLINK "https://www.science.org/doi/abs/10.1126/science.adq7280"](https://www.science.org/doi/abs/10.1126/science.adq7280)]
- Gulev, S. K., et al. (2021). Changing state of the climate system. In V. Masson-Delmotte et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 287–422). Geneva: Intergovernmental Panel on Climate Change.
- Hansen J and P Karecha (2025) Large cloud feedback confirms high sensitivity. [[HYPERLINK "https://www.columbia.edu/~jeh1/mailings/2025/CloudFeedback.13May2025.pdf"](https://www.columbia.edu/~jeh1/mailings/2025/CloudFeedback.13May2025.pdf)]
- Hegerl, G. C., et al. (2007). Understanding and attributing climate change. In S. Solomon et al. (Eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 663–745). Cambridge University Press.
- Hegerl, GC, S Bronniman, A Schurer et al. (2017) Early 20th century warming: Anomalies, causes and consequences. *WIREs Climate Change*, DOI: 10.1002/wcc.522
- Hegerl, GC, S Bronniman, T Cowan (2019) Causes of climate change over the historical record. *Environmental Research Letters*, 14, 123006
- Hodnebrog, Ø et al. (2024), Recent reductions in aerosol emissions have increased Earth's energy imbalance. *Communications Earth and Environment* 5, 166 (2024). doi:10.1038/s43247-024-01324-8
- Houghton, J. T., et al. (Eds.). (2001). *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1–881). Cambridge University Press. [[HYPERLINK "https://mailchi.mp/caa/large-cloud-feedback-confirms-high-climate-sensitivity"](https://mailchi.mp/caa/large-cloud-feedback-confirms-high-climate-sensitivity)]
- Kravtsov, S., Westgate, A., & Gavrilov, A. (2024). Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics*, 62, 10281–10306. [[HYPERLINK "https://doi.org/10.1007/s00382-024-07451-4"](https://doi.org/10.1007/s00382-024-07451-4)]
- Kuchar, A., Sukhodolov, T., Chiodo, G., Jörimann, A., Kult-Herdin, J., Rozanov, E., and Rieder, H. H. (2025): Modulation of the northern polar vortex by the Hunga Tonga–Hunga Ha'apai eruption and the associated surface response, *Atmospheric Chemistry and Physics*, 25, 3623–3634, [[HYPERLINK "https://doi.org/10.5194/acp-25-3623-2025"](https://doi.org/10.5194/acp-25-3623-2025)].

- Lewis, Nicholas (2023) “Objectively Combining Climate Sensitivity Evidence,” *Climate Dynamics* 61, no. 9–10 (2023): 3155–3163, [HYPERLINK "<https://doi.org/10.1007/s00382-022-06398-8>"].
- Lockwood, M. (2012). Solar influence on global and regional climates. *Surveys in Geophysics*, 33(3–4), 503–534. [HYPERLINK "<https://doi.org/10.1007/s10712-012-9181-3>"]
- Loeb, N. G. *et al.* (2019) Decomposing Shortwave Top-of-Atmosphere and Surface Radiative Flux Variations in Terms of Surface and Atmospheric Contributions. *Journal of Climate* 32(16), 5003–5019 (2019). doi:10.1175/JCLI-D-18-0826.1
- Loeb, N., S-H Ham, RP Allen, T J Thorsen, B Meyssignac, S Kato, GC Johnson, JL Lyman (2024) Observational Assessment of Changes in Earth’s Energy Budget since 2000. *Surveys in Geophysics*, 45, 1757-1783
- Mass, C., *et al.* (2024). The Pacific Northwest heat wave of 25–30 June 2021: Synoptic/mesoscale conditions and climate perspective. *Weather and Forecasting*, 39(2), 275–291. [HYPERLINK "<https://doi.org/10.1175/WAF-D-23-0154.1>"]
- Matthes, K., *et al.* (2017). Solar forcing for CMIP6 (v3.2). Geoscientific Model Development, 10(6), 2247–2302. [HYPERLINK "<https://doi.org/10.5194/gmd-10-2247-2017>"]
- McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophysical Research Letters*, 49, e2022GL100380. [HYPERLINK "<https://doi.org/10.1029/2022GL100380>"]
- McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophysical Research Letters*, 49, e2022GL100380. [HYPERLINK "<https://doi.org/10.1029/2022GL100380>"]
- McKittrick, R. (2021). Checking for model consistency in optimal fingerprinting: A comment. *Climate Dynamics*, 58(1–2), 405–411. [HYPERLINK "<https://doi.org/10.1007/s00382-021-05913-7>"]
- McKittrick, R. (2023). Total least squares bias in climate fingerprinting regressions with heterogeneous noise variances and correlated explanatory variables. *Environmetrics*, 35(2), e2835. [HYPERLINK "<https://doi.org/10.1002/env.2835>"]
- McKittrick, Ross R (2022) [HYPERLINK "<https://link.springer.com/article/10.1007/s00382-022-06315-z>" \t "_blank"]. *Climate Dynamics* 10.1007/s00382-022-06315-z
- McKittrick, Ross R (2025) Consistent Climate Fingerprinting. *Climate Dynamics* forthcoming preprint available at [HYPERLINK "<http://www.rossmckittrick.com>"]
- McLean, J.D., C. R. de Freitas, and R. M. Carter, (2009) “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
- Miralles, Ophélie and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 [HYPERLINK "<https://doi.org/10.1016/j.wace.2023.100584>"]
- Myhre, G., D. Shindell, F.-M. Bréon, *et al* (2013): Anthropogenic and Natural Radiative Forcing. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., *et al.* (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Nissan, Hannah, Lisa Goddard, Erin Coughlan de Perez, *et al.* (2019) On the use and misuse of climate change projections in international development. *Wires Climate Change* 14 March 2019 [HYPERLINK "<https://doi.org/10.1002/wcc.579>"]

- Palmer, Tim N and Bjorn Stevens (2019) The scientific challenge of understanding and estimating climate change. *Proceedings of the National Academy of Sciences* 116 (49) 24390-24395 [HYPERLINK "<https://doi.org/10.1073/pnas.1906691116>"]
- Pearl, J. (2009). *Causality*. Cambridge University Press.
- Philip, S. Y., *et al.* (2022). Rapid attribution analysis of the extraordinary heatwave on the Pacific coast of the U.S. and Canada June 2021. *Earth System Dynamics*, 13(4), 1689–1713. [HYPERLINK "<https://doi.org/10.5194/esd-13-1689-2022>"]
- Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay [HYPERLINK "<https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>"]
- Ranasinghe, R., Ruane, A. C., Vautard, R., Arnell, N., Coppola, E., Cruz, F. A., ... Zaaboul, R. (2021). Chapter 12: Climate change information for regional impact and for risk assessment. In V. Masson-Delmotte *et al.* (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1767–1926). Cambridge University Press. [HYPERLINK "<https://doi.org/10.1017/9781009157896.014>"]
- Razzak, Weshah A. (2022). "The Econometrics of Global Warming," *Journal of Economics and Econometrics*, vol. 65(2), pages 13-47.
- Sardeshmukh, P. D., Compo, G. P., & Penland, C. (2015). Need for caution in interpreting extreme weather statistics. *Journal of Climate*, 28(23), 9166–9187. [HYPERLINK "<https://doi.org/10.1175/JCLI-D-15-0020.1>"]
- Scafetta, N. (2013). Discussion on climate oscillations: CMIP5 general circulation models versus a semi-empirical harmonic model based on astronomical cycles. *Earth-Science Reviews*, 126, 321
- Scaffeta, Nicola (2021) "Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature," *Atmosphere* 12, no. 2: 147, [HYPERLINK "<https://doi.org/10.3390/atmos12020147>"]
- Schmidt, G. (2024) Climate models can't explain 2023's huge heat anomaly — we could be in uncharted territory. *Nature* 627, 467. [HYPERLINK "<https://www.nature.com/articles/d41586-024-00816-z>"]
- Schmutz, Werner K. (2021) "Changes in the Total Solar Irradiance and Climatic Effects," *Journal of Space Weather and Space Climate* 11: 40, <https://doi.org/10.1051/swsc/2021016>.
- Seneviratne, S. *et al.* (2021) "Chapter 11: Weather and Climate Extreme Events in a Changing Climate." In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, *et al.*, 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
- Solanki, S.K. *et al.* (2004), "Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years," *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, [HYPERLINK "<https://doi.org/10.1038/nature02995>"].
- Stefani, Frank (2021) "Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions," *Climate* 9, no. 11 (November 3, 2021): 163, [HYPERLINK "<https://doi.org/10.3390/cli9110163>"].
- Thompson, DJW, JM Wallace, JJ Kennedy, PD Jones (2010) An abrupt drop in Northern Hemisphere Sea Surface Temperature around 1970. *Nature*, 467, 444-447

- Tokina, H, SP Xie, and H Mukougawa (2017) Early 20th century Arctic warming intensified by Pacific and Atlantic multidecadal variability. *Proceedings of the National Academy of Sciences*, 114, 6227-6233 [HYPERLINK "<https://www.pnas.org/doi/abs/10.1073/pnas.1615880114>"]
- Tung, Ka-Kit and Jiansong Zhou (2013) “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
- Usoskin, I.G., S. K. Solanki, and G. A. Kovaltsov (2007) “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, [HYPERLINK "<https://doi.org/10.1051/0004-6361:20077704>"].
- Velasco Herrera, V.M., B. Mendoza, and G. Velasco Herrera (2015) “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
- Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 [HYPERLINK "<https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>"]
- World Weather Attribution (2021) “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
- Yuan, *et al.* (2024) Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Communications Earth and Environment* 5, 281 (2024). doi:10.1038/s43247-024-01442-3
- Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. [HYPERLINK "<https://doi.org/10.1029/2023GL104090>"]

OUO – Official Use Only

PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

9 CLIMATE CHANGE AND U.S. AGRICULTURE

Chapter summary

There has been abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. The increase in ambient CO₂ has also boosted productivity of all major U.S. crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from, or be harmed by, climate change, once the adaptive responses of farmers are considered the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn *et al.* (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn *et al.* method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached conclusions similar to Mendelsohn *et al.* (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the U.S. agricultural sector. However, a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in U.S. agriculture due to climate warming.

Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and

20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2, CO₂ is a major driver of plant growth, so this omission biases the analysis towards underestimation of the benefits of climate change to agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiments” or FACE plots, in which small sources of CO₂ are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth *et al.* (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm caused an average 18 percent increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key U.S. agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max*(L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations improved photosynthesis rate, water use efficiency, and growth Li (2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. There were also ten studies reporting on +600 ppm CO₂ enrichment, which increased photosynthesis by an average of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr., 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41 percent loss of growth under ambient CO₂ but only a 13 percent loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured both the yield and nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16 percent but a 7 percent decrease in grain protein levels. But they also found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection, growers could select wheat types that best take advantage of the elevated CO₂.

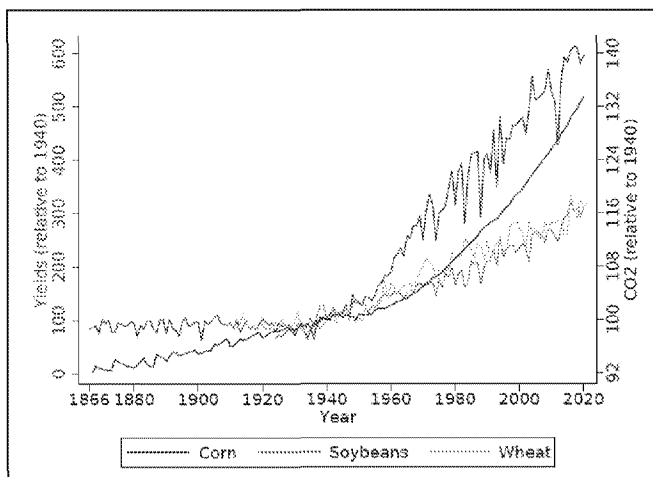


Figure 9.1: U.S. average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100. Source: Taylor and Schlenker (2021)

Further evidence

A 2021 report from the U.S. National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted U.S. crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

Beyond growth benefits, extra CO₂ boosts plant resilience to dryness. Deryng *et al.* (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for maize (corn), wheat, rice and soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them; once fertilization was taken into account, all regions showed a net CWP gain. Deryng *et al.* also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains and mitigated by up to 90 percent for rice and 60 percent for maize. Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng *et al.* (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, observations show the opposite: greening is happening even in arid areas. Zhang *et al.* (2024) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4 percent of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the U.S. Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based largely on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore *et al.*, 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore *et al.* (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore *et al.* projected declining global crop yields for all crop types in all regions due to warming.

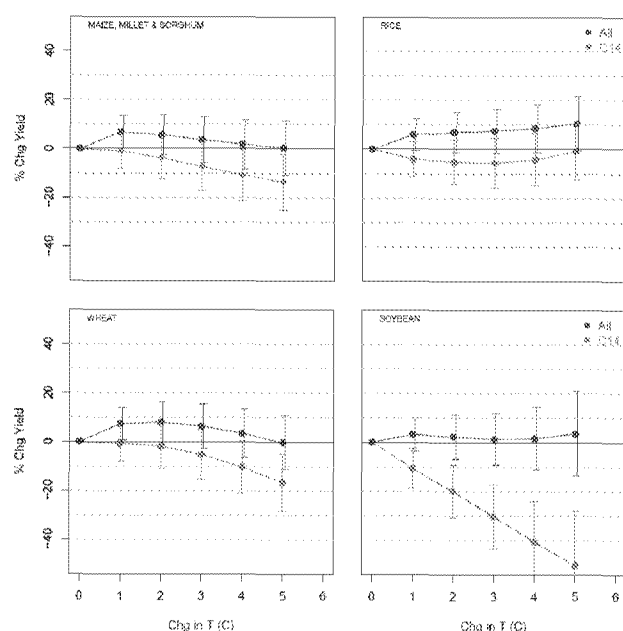


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore *et al.* (2017). Green: after including omitted data. Source: McKittrick (2025).

McKittrick (2025) re-examined the Moore *et al.* database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the records most commonly missing were the changes in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables, thereby increasing the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 9.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

9.4 CO₂ fertilization and nutrient loss

Evidence has shown that CO₂-induced biomass gains are sometimes accompanied by reductions in the concentrations of protein and other key nutrients such as iron and zinc (Ebi *et al.* 2021). Some experimental evidence has shown that the rising temperatures expected to accompany higher CO₂ levels will offset this loss (Köhler *et al.* 2019) although the evidence for this is mixed, as is the evidence that nutrient dilution observed to date is attributable to higher CO₂ (Ziska 2022). If nutrient dilution does occur under rising CO₂ levels there are several adaptive strategies that could be pursued.

First, selective breeding to raise micronutrient content is already long established (Saltzman *et al.* 2017) and has proven to be a cost-effective agronomic strategy (Ebi *et al.* 2021). Strategies can include both conventional breeding and genetically-modified organisms. An example of the latter is Golden Rice, which contains elevated levels of beta-carotene to boost biosynthesis of vitamin A in the human body. Optimal strategies will be location-specific because they vary by crop, climate and soil type (Ebi *et al.* 2021). Second, fortification of food products with micronutrients is already routine. Folic acid (a B vitamin) is added to flour and many other foods; iodine is added to table salt, most commercial breakfast cereals are fortified with iron and numerous vitamins, *etc.* Third, dietary supplements in the form of multivitamin tablets are inexpensive, widely-available and routinely consumed.

One concern about reliance on adaptive strategies is whether they are feasible in low-income countries. Micronutrient deficiency is already a problem in the developing world and dietary supplements have proven to be an effective low-cost response (Ebi *et al.* 2021). It should also be noted the IPCC emission scenarios that generate high levels of warming do so on the basis of high levels of income growth. The SSP scenarios³ assume that, compared to 2005 levels, global per capita income will double by 2100 in the lowest growth case (SSP3), and in the highest emission case (SSP5) global per-capita income will grow nearly 16-fold. In that scenario even the poorest regions (Africa and the Middle East) end up with a per capita income of about US\$126,000, 70 percent higher than current U.S. per capita income (about US\$75,000). Consequently the same scenarios in which CO₂ levels increase the most are also those in which global poverty is largely eliminated, in which case all countries would be able to afford dietary supplements as necessary to address micronutrient deficiencies, if they arise and cannot be addressed using on-farm agricultural strategies.

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. To the extent nutrient dilution occurs there are mitigating strategies available that will need to be researched and adapted to local conditions.

References

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* [HYPERLINK "<https://doi.org/10.1111/gcb.15375>"]
- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Bareille, F. and R. Chakir (2023) The impact of climate change on agriculture: A repeat-Ricardian analysis. *Journal of Environmental Economics and Management* 119
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.

³ See compilation at [HYPERLINK "<https://ourworldindata.org/explorers/ipcc-scenarios?Metric=GDP&Sub-metric=Total+radiative+forcing&Region=Global&country=SSP1+-+Baseline-SSP2+-+Baseline-SSP3+-+Baseline-SSP4+-+Baseline-SSP5+-+Baseline>"].

- Burke, Marshall and Kyle Emerick (2016) Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy* 8(3) August 2016 106–140 [[HYPERLINK "https://www.aeaweb.org/articles?id=10.1257/pol.20130025"](https://www.aeaweb.org/articles?id=10.1257/pol.20130025)]
- Cheng, L., Zhang, L., Wang, YP. *et al.* Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* 8, 110 (2017). [[HYPERLINK "https://doi.org/10.1038/s41467-017-00114-5"](https://doi.org/10.1038/s41467-017-00114-5)]
- CO2Science.org (undated) Plant growth archive
http://www.co2science.org/data/plant_growth/dry/dry_subject_b.php
- Deryng, D., Elliott, J., Folberth, C. *et al.* (2021) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 6, 786–790 (2016). [[HYPERLINK "https://doi.org/10.1038/nclimate2995"](https://doi.org/10.1038/nclimate2995)]
- Deschênes, Olivier and Michael Greenstone (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply to Comment *American Economic Review*. 102, no. 7: 3761–3773. [[HYPERLINK "http://hdl.handle.net/1721.1/82641"](http://hdl.handle.net/1721.1/82641)]
- Ebi, Kristie L, C Leigh Anderson, Jeremy J Hess, *et al.* (2021) Nutritional quality of crops in a high CO₂ world: an agenda for research and technology development. *Environmental Research Letters* 16(6) 064045 [[HYPERLINK "https://iopscience.iop.org/article/10.1088/1748-9326/abfcfa"](https://iopscience.iop.org/article/10.1088/1748-9326/abfcfa)]
- Köhler, Iris H., Steven C. Huber, Carl J. Bernacchi, Ivan R. Baxter (2019) Increased temperatures may safeguard the nutritional quality of crops under future elevated CO₂ concentrations. *The Plant Journal* 97(5) 872–886 [[HYPERLINK "https://onlinelibrary.wiley.com/doi/epdf/10.1111/tpj.14166"](https://onlinelibrary.wiley.com/doi/epdf/10.1111/tpj.14166)]
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (Glycine max (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105–112.
- McKittrick, Ross R. (2025) Extended Crop Yield Meta-analysis Data do not Support Upward SCC Revision. *Scientific Reports* 15 article 5575 [[HYPERLINK "https://www.nature.com/articles/s41598-025-90254-2"](https://www.nature.com/articles/s41598-025-90254-2)]
- Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, Sept 1994 753–771.
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>
- Ortiz-Bobea, Ariel (2019) The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture. *American Journal of Agricultural Economics*. 102 (3), 934–959.
- Saltzman, Amy, Ekin Birol, Adewale Oparinde *et al.* (2017) Availability, production, and consumption of crops biofortified by plant breeding: current evidence and future potential. *Annals of the New York Academy of Sciences* Volume 1390, Issue 1 [[HYPERLINK "https://doi.org/10.1111/nyas.13314"](https://doi.org/10.1111/nyas.13314)]
- Schlenker, Wolfram and Michael Roberts (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* 106 (37) 15594–15598 [[HYPERLINK "https://doi.org/10.1073/pnas.0906865106"](https://doi.org/10.1073/pnas.0906865106)]
- Taylor, Charles and Wolfram Schlenker (2023) Environmental drivers of agricultural productivity growth: CO₂ fertilization of US field crops. National Bureau of Economic Research Working paper 29320, [[HYPERLINK "http://www.nber.org/paper/w29320"](http://www.nber.org/paper/w29320)]
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, “Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review”, EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, Nov. 2023, [[HYPERLINK "https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf"](https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf)]
- Zhang *et al.* (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 [[HYPERLINK "https://www.nature.com/articles/s43247-024-01463-y"](https://www.nature.com/articles/s43247-024-01463-y)]

Ziska, Lewis H (2022) Rising Carbon Dioxide and Global Nutrition: Evidence and Action Needed. *Plants* 1(7), 1000; [HYPERLINK "<https://doi.org/10.3390/plants11071000>"]

10 MANAGING RISKS OF EXTREME WEATHER

Chapter summary

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The U.S. economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase if people are able to undertake adaptive responses.

10.1 Socioeconomic context

Risks from human-caused climate change are affected by natural weather and climate variability and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as U.S. population grew from 76 million in 1900 to over 331 million in 2020 (Goklany 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01 percent of the U.S. population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006 percent of the U.S. population) (NOAA National Hurricane Center 2025; U.S. Census Bureau 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang 2023). U.S. weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (Molina and Rudik 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992), have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (Battelle Memorial Institute 2013). Inland dams in the U.S. help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During

Hurricane Helene (2024), TVA’s strategies prevented approximately \$406M in potential damages (APPA 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1 Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the U.S., so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster as a proportion of GDP have decreased by about 80 percent since 1980, as shown in Figure 10.1. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments, NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (Pielke Jr., 2025).

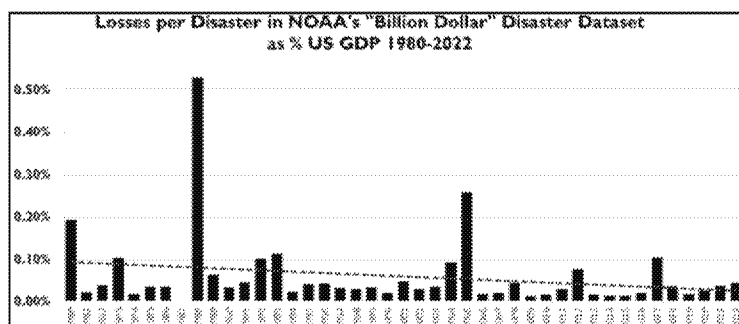


Figure 10.1: Losses per disaster as a % of Gross Domestic Product in NOAA's billion-dollar disaster dataset (the version downloaded in July 2023), 1980 to 2022. Source: (Pielke, Jr. 2024)

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. Finally, the U.S. economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period, though not in the continental U.S. (Chapter 6), and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes typically stems from hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao *et al.* 2021, Ritchie 2024). Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini *et al.* 2015, Lee and Dessler 2023). The U.S. EPA (citing data from the Centers for Disease Control) reports that on average over 1999 to 2015 there were 2.2 deaths per million Americans for which cold was listed as the main underlying cause and an additional 2.4 deaths per million for which cold was listed as a contributing factor (EPA 2025). By contrast there were 1.3 deaths per million for which heat was the main cause and an additional 0.8 per million for which it was a contributor. By this metric cold accounts for approximately double the weather-related deaths as does heat.

Epidemiological methods that consider correlational evidence, not just death certificate reports, indicate the cold/warm ratio might be much higher. A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7 percent of deaths were attributable to sub-optimal temperatures, of which 7.4 percent were attributable to cold and only 0.4 percent were attributable to heat (Gasparini *et al.* 2015). In other words, cold weather killed 18.5 times as many people as did hot weather.

Figure 10.2 shows the distribution of results from Gasparini *et al.* (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9 percent, of which 5.5 percent was due to cold, thus cold weather killed 14 times as many people as hot weather.

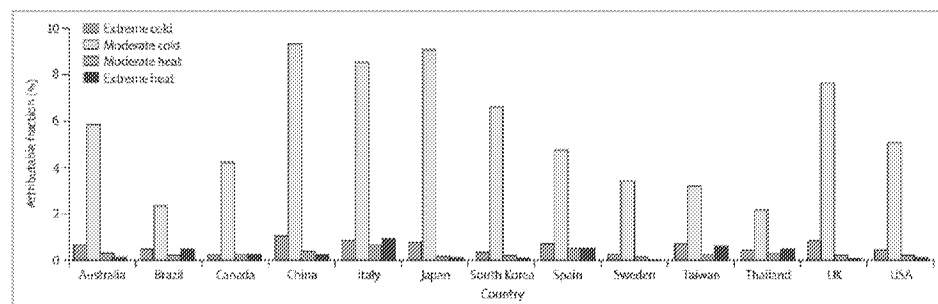


Figure 10.2. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini *et al.* (2015).

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86 percent of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis *et al.* (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb *et al.* (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60 percent decline in average heat-related mortality over the period 1987–2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio *et al.* (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, rising temperatures are associated with a net saving of lives since they reduce mortality from cold events. The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill *et al.* 2022) acknowledges that heat-related mortality risk is declining over time:

Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.

Yet the IPCC misrepresents the overall situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

The observed decline in U.S. heat-related mortality has been specifically attributed to adaptation. Wang *et al.* (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live, Wang *et al.* (2018) project not only no increase in heat-related mortality, but an overall mortality *decrease* for the U.S. as a whole. They conclude that

Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.

10.3.2 Mortality risks and energy costs

A 2016 study of U.S. long term mortality risks associated with temperature variations (Barreca *et al.* 2016) showed that increases in mortality across the U.S. are associated with both cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus *et al.* (2022) showed that wealthy and poor households in the U.S. adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($> 30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

References

- Allen, M.J. and S.C. Sheridan (2018) Mortality risks during extreme temperature events (ETEs) using a distributed lag non-linear model. (2018) *International Journal of Biometeorology* 62, 57–67 (2018). [HYPERLINK "<https://doi.org/10.1007/s00484-015-1117-4>"]
- American Public Power Association. (APPA, 2024, March 7). TVA flood mitigation strategies prevented approximately \$406 million in potential damages. Public Power Current. [HYPERLINK "<https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>" \t "_new"]
- Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro (2016), Adapting to climate change: The remarkable decline in the US temperature mortality relationship over the twentieth century, *Journal of Political Economy*, 2016, 124 (1), 105–159.
- Battelle Memorial Institute. (2013, December). Final independent external peer review report: Hurricane Isaac (2012) assessment (Prepared for U.S. Army Corps of Engineers, New Orleans District). [HYPERLINK "<https://www.mvn.usace.army.mil/Portals/56/docs/PD/PeerReview/TCN13-003HurIsaacAssessIEPRFinal.pdf>" \t "_new"]
- Bobb JF, RD Peng, ML Bell and F Dominici (2014) Heat-related mortality and adaptation to heat in the United States. *Environmental Health Perspectives* 122:811–816; [HYPERLINK "<https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.1307392>"]
- Davis, Robert E., Paul C. Knappenberger, Patrick J. Michaels and Wendy M. Novicoff (2003) “Changing Heat-Related Mortality in the United States” *Environmental Health Perspectives* 111(14) November 2003 pp. 1712—1718 [HYPERLINK "<https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.6336>"]
- Deryugina, T., & Hsiang, S. M. (2023). Does the environment still matter? Daily temperature and income in the United States (NBER Working Paper No. 31361). National Bureau of Economic Research. [HYPERLINK "<https://www.nber.org/papers/w31361>" \t "_new"]
- Doremus, JM, I. Jacqz and S. Johnston (2022), “Sweating the energy bill: Extreme weather, poor households, and the energy spending gap.” *Journal of Environmental Economics and Management*, doi: [HYPERLINK "<https://doi.org/10.1016/j.jeem.2022.102609>"] .
- Environmental Protection Agency (2025) Climate Change Indicators. [HYPERLINK "<https://www.epa.gov/climate-indicators/view-indicators>"]
- Federal Emergency Management Agency (FEMA). (2020, February 13). The role of Florida’s building codes in Hurricane Michael recovery. [HYPERLINK "<https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael>" \t "_new"]

- Gasparini, A., Y. Guo, M. Hashizume *et al.* (2015) Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet* 386: 369-385 July 25, 2015 [HYPERLINK "[http://dx.doi.org/10.1016/S0140-6736\(14\)62114-0](http://dx.doi.org/10.1016/S0140-6736(14)62114-0)"]
- Goklany, I. M. (2011). Deaths from extreme weather events, 1900–2010. Reason Foundation. [HYPERLINK "https://a8d50b36.delivery.rocketcdn.me/wp-content/uploads/2011/09/deaths_from_extreme_weather_1900_2010.pdf" \t "_new"]
- Lee, Jangho and Andrew Dessler (2023) Future Temperature-Related Deaths in the U.S.: The Impact of Climate Change, Demographics, and Adaptation. *GeoHealth* 7(8) August 2023 [HYPERLINK "<https://doi.org/10.1029/2023GH000799>"]
- Molina, R and I Rudik (2024) The value of improving hurricane forecasts. *National Bureau of Economic Research Working Paper* 32548 June 2024. [HYPERLINK "<https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>"]
- National Hurricane Center. (n.d.). Costliest U.S. tropical cyclones tables updated. NOAA National Hurricane Center. Retrieved May 8, 2025, from [HYPERLINK "<https://www.nhc.noaa.gov/outreach/history/>" \t "_new"]
- National Research Council. (2010). Adapting to the impacts of climate change. The National Academies Press. [HYPERLINK "<https://nap.nationalacademies.org/read/12888/chapter/2>" \t "_new"]
- Nordio, Francesco, Antonella Zanobetti, Elena Colicino, Itai Kloog and Joel Schwartz (2015). “Changing patterns of the temperature–mortality association by time and location in the US, and implications for climate change” *Environment International* Volume 81, pp 80-86 [HYPERLINK "<https://doi.org/10.1016/j.envint.2015.04.009>"].
- O'Neill, B., *et al.* (2022). Key risks across sectors and regions. In AR6 Working Group II *Climate Change 2022: Impacts, Adaptation and Vulnerability* (pp. 2411–2538). Intergovernmental Panel on Climate Change. [HYPERLINK "<http://www.ipcc.ch>"]
- Pielke Jr., R. (2024). Scientific integrity and U.S. 'billion dollar disasters'. *npj Natural Hazards*, 1, Article 12. [HYPERLINK "<https://www.nature.com/articles/s44304-024-00011-0>" \t "_new"]
- Pielke Jr., R. (2025, May 8). RIP NOAA's billion dollar disasters. The Honest Broker [Substack]. [HYPERLINK "<https://rogerpielkejr.substack.com/p/rip-noaas-billion-dollar-disasters>" \t "_new"]
- Ritchie, H. (2024). How many people die from extreme temperatures, and how this could change in the future: Part one. Our World in Data. [HYPERLINK "<https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>" \t "_new"]
- Tennessee Valley Authority (TVA). (n.d.). Flood management. Retrieved May 8, 2025, from [HYPERLINK "<https://www.tva.com/environment/managing-the-river/flood-management>" \t "_new"]
- U.S. Census Bureau. (n.d.). Decennial census by decade. Retrieved May 8, 2025, from [HYPERLINK "<https://www.census.gov/programs-surveys/decennial-census/decade.html>" \t "_new"]
- Wang, Yan, Francesco Nordio, John Nairn, Antonella Zanobetti and Joel D. Schwartz (2018) “Accounting for adaptation and intensity in projecting heat wave-related mortality” *Environmental Research* 161 pp. 464—471. [HYPERLINK "<https://doi.org/10.1016/j.envres.2017.11.049>"]

Zhao, Q., *et al.* (2021). Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: A three-stage modelling study. *The Lancet Planetary Health*, 5(7). [HYPERLINK "[https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4)" \t "_new"]

11 CLIMATE CHANGE, THE ECONOMY, AND THE SOCIAL COST OF CARBON

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in AR5. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy and that trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries, but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points does not justify major revisions to SCC estimates.

11.1 Climate change and economic growth

11.1.1 Overview

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus, 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued

that any effects of climate change on U.S. economic activity would be small relative to the many other changes that would happen (Schelling 1992).

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report (Arent *et al.* 2014, emphasis added)

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

Evidence since AR5 does not change this assessment. Mohaddes *et al.* (2023) found that warm weather shocks have small negative effects on U.S. state-level output but not income, while cold weather shocks negatively affect both and the impacts are about four times larger, implying a shift to warmer conditions would, if anything, yield a net economic benefit for the U.S.

These statements are validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty.

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen, 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr., 2018, 2020) as have mortality risks (Formetta and Feyen, 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick, 2015). Nor have past extreme weather events had a significant effect on U.S. banks' performance (Blickle *et al.*, 2021); warming has even been shown to be beneficial for the finance and

insurance sector (Mohaddes *et al.* 2023). Figure 11.1 below is illustrative. For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it (Storm 2017):

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

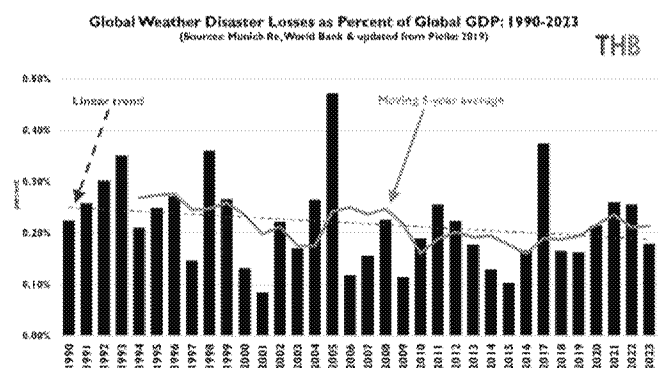


Figure 11.1 Global weather losses as a fraction of GDP. Source: Pielke Jr. (2023)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future, 2025). Nordhaus’ work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus, 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus’ Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of

DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we modestly scale back fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even more costly.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

11.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell *et al.* (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke *et al.* (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao *et al.* (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer *et al.* (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang *et al.* (2023) updated the DJO12 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell *et al.* (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke *et al.* (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke *et al.* (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95 percent confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is considered the original temperature effects reported by Dell *et al.* became small and insignificant.

Berg *et al.* (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall, they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100, even using the extreme RCP8.5 scenario, they computed the average global GDP loss would be only 1.9 percent compared to a scenario with no warming. That is, instead of the economy growing 400 percent it would grow 392%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 392 percent growth.

To summarize, economists consider climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust (Tol 2024). Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

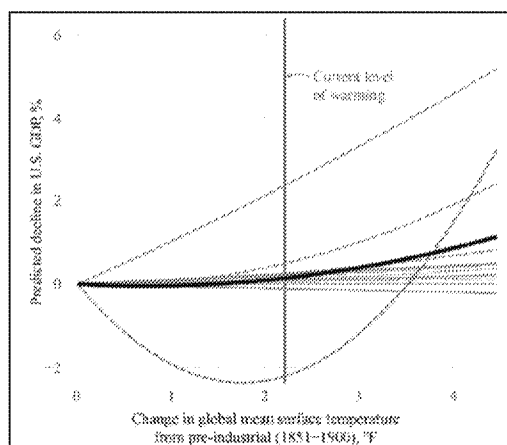


Figure 11.2: Decline in U.S. GDP per degree of warming. Source: CEA-OMB (2023)

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. Figure 11.2, from a 2023 CEA-OMB report, shows the expected decrement in U.S. GDP as a

function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe on the U.S. GDP is indeed negligible.

11.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

11.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many, if not most, of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with a changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordhaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0 percent GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5 percent for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past

hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this might fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

11.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. The most recent data-driven ECS values tend to be lower than this (see Chapter 4). Dayaratna *et al.* (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 9) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg *et al.* 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.

- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the U.S. Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore *et al.* (2017). But as discussed in Chapter 9, McKittrick (2025) showed that Moore *et al.* (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

11.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 9 looked at climate change and U.S. agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. Haverd *et al.* (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna *et al.* (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF⁴ value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle, 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

11.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon

⁴ Marginal Cost of Public Funds: the optimal carbon tax rate is the SCC divided by the MCPF (Sandmo 1977).

(SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz *et al.*, 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example, an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford, 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example, a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen *et al.* 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford, 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the second type is a possibility. Kypke *et al.* (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon, 2023).

The possible existence of bifurcations in the Earth’s climate system implies abrupt transitions are possible, not just in response to large forcing but also to small perturbations. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos *et al.*, 2024) and indeed might not be able to since one implication of the “butterfly effect” is the existence of predictability boundaries of nonlinear systems (Palmer *et al.*, 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict it or prevent it from happening.

AR6 (WGI, Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the “tipping point” concept in discussions of climate change (see [[HYPERLINK "https://report-2023.global-tipping-points.org/what-is-a-tipping-point/"](https://report-2023.global-tipping-points.org/what-is-a-tipping-point/)] for example). As summarized by AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton *et al.*, 2023). It identifies more than 25 parts of the

climate system said to constitute tipping points. What gets classified as a climate “tipping point” is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of parts of the Greenland and West Antarctic ice sheets. These impacts can reverse on the decadal and century timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). AR6 WG1 Summary for Policy Makers states:

The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is *high confidence* in the 21st century decline, there is only *low confidence* in the magnitude of the trend. There is *medium confidence* that there will not be an abrupt collapse before 2100. (C.3.4)

There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5). (B.5.2)

For the purpose of SCC calculations, the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz *et al.* incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However, the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there might be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been considered, the result is only a modest increase in the SCC value in the 21st century.

11.2.5 Are there alternatives?

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung, 2017) stated it’s “time to kill it” due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for “target-consistent” carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However, the uncertainty of SCC estimates doesn’t mean that other regulatory measures are inherently better or more efficient. Many emissions regulations (such as

electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) cost far more per tonne of abatement than any mainstream SCC estimate, which is sufficient to establish that they fail a cost-benefit test.

References

- AR6: *Intergovernmental Panel on Climate Change Sixth Assessment Report* (2021) Working Group I Contribution. [HYPERLINK "<http://www.ipcc.ch>"].
- Arent, D.J., R.S.J. Tol, E. Faust, J.P. Hella, S. Kumar, K.M. Strzepek, F.L. Tóth, and D. Yan (2014) Key economic sectors and services. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 659-708.[HYPERLINK "https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap10_FINAL.pdf"]
- Barker, D. (2023) Temperature Shocks and Economic Growth: Comment on Dell, Jones, and Olken. *Econ Journal Watch* 20(2) 234-253 [HYPERLINK "<https://econjwatch.org/articles/temperature-shocks-and-economic-growth-comment-on-dell-jones-and-olken>"]
- Barrage, Lint and William Nordhaus (2024) Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. *Proceedings of the National Academy of Sciences* 121 (13) e2312030121 [HYPERLINK "<https://doi.org/10.1073/pnas.2312030121>"]
- Berg, Kimberly, Chadwick C Curtis and Nelson Mark. (2021) GDP and temperature: Evidence on cross-country response heterogeneity. NBER Working Paper 31327 June 2023 [HYPERLINK "<http://www.nber.org/papers/w31327>"]
- Blickle, Kristian; Sarah N. Hamerling, and Donald P. Morgan (2021) : How bad are weather disasters for banks?, Staff Reports, No. 990, Federal Reserve Bank of New York, New York, NY [HYPERLINK "<https://www.econstor.eu/bitstream/10419/247913/1/sr990.pdf>"]
- Brunetti, Maura and Charline Ragon (2023) Attractors and bifurcation diagrams in complex climate models. *Physical Review E* 107 054214 [HYPERLINK "<https://journals.aps.org/pre/abstract/10.1103/PhysRevE.107.054214>"]
- Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.
- Council of Economic Advisors-Office of Management and Budget (CEA-OMB 2023) Methodologies and considerations for integrating the physical and transition risks of climate change into macroeconomic forecasting for the president's budget. March 13, 2023. [HYPERLINK "<https://bidenwhitehouse.archives.gov/wp-content/uploads/2023/03/CEA-OMB-White-Paper.pdf>"]
- Crawford, John D (1991) Introduction to Bifurcation Theory. *Reviews of Modern Physics* 63(4) October 1991 991—1037.
- Dakos, Vasilis, Chris Boulton, Joshua Buxton *et al.* (2024) Tipping point detection and early warnings in climate, ecological, and human systems. *Earth System Dynamics* 15 1117—1135 [HYPERLINK "<https://doi.org/10.5194/esd-15-1117-2024>"]
- Dayaratna, Kevin and Ross McKittrick (2023) "Reply to comment on "climate sensitivity, agricultural productivity and the social cost of carbon in fund" by Philip Meyer" *Environmental Economics and Policy Studies* 2023 link.springer.com/article/10.1007/s10018-023-00364-2
- Dayaratna, Kevin, Ross McKittrick and David Kreutzer (2017) Empirically-Constrained Climate Sensitivity and the Social Cost of Carbon. *Climate Change Economics* April 2017 DOI: [HYPERLINK "<http://dx.doi.org/10.1142/S2010007817500063>"]

- Dayaratna, Kevin, Ross McKittrick and Patrick J. Michaels (2020) Climate Sensitivity, Agricultural Productivity and the Social Cost of Carbon in FUND. *Environmental Economics and Policy Studies* <https://doi.org/10.1007/s10018-020-00263-w>
- Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American economic journal: Macroeconomics*, 4(3):66–95, 2012. ISSN 1945-7707.
- Dietz, S., J. Rising, T. Stoerk, G. Wagner (2021) Economic impact of tipping points in the climate system. *Proceedings of the National Academy of Science* 2021 Vol. 118 No. 34 e2103081118
- Dunne, Daisy (2017), “Q&A: The Social Cost of Carbon,” Carbon Brief, February 14, 2017, [HYPERLINK "<https://www.carbonbrief.org/qa-social-cost-carbon/>"]
- Formetta, Giuseppe and Luc Feyen (2019) Empirical evidence of declining global vulnerability to climate-related hazards. *Global Environmental Change* 57 101920 [HYPERLINK "<https://doi.org/10.1016/j.gloenvcha.2019.05.004>"]
- Greßer, Christina, Daniel Meierrieks, and David Stadelmann (2021) The link between regional temperature and regional incomes: econometric evidence with sub-national data. *Economic Policy*, 36(107):523–550, 2021.
- Haverd, V., Raupach, M., Briggs, P., *et al.* (2020). Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology*, 26, 2390–2402.
- Hu, Bin and Ross McKittrick (2015) Climatic Variations and the Market Value of Insurance Firms. *Journal of Insurance Issues* Vol. 39, No. 1, pp. 92-111 [HYPERLINK "<https://www.jstor.org/stable/43741103>"]
- Kypke, K. L., Langford, W. F., and Willms, A. R.: Anthropocene climate bifurcation, *Nonlinear Processes in Geophysics*, 27, 391–409, <https://doi.org/10.5194/npg-27-391-2020>, 2020.
- Lavelle, Marianne (2019) Carbon Tax Plans: How They Compare and Why Oil Giants Support One of Them. *Inside Climate News* March 7, 2019 [HYPERLINK "<https://insideclimatenews.org/news/07032019/carbon-tax-proposals-compare-baker-shultz-exxon-conocophillips-ccl-congress/>"]
- Lenton, T.M., D.I. Armstrong McKay, *et al.* (eds) (2023) *The Global Tipping Points Report 2023*. University of Exeter, Exeter, UK. [HYPERLINK "<https://report-2023.global-tipping-points.org/>"]
- Lewis, N., (2013) An objective Bayesian, improved approach for applying optimal fingerprint techniques to estimate climate sensitivity. *Journal of Climate*, 26, 7414-7429. [HYPERLINK "<https://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00473.1>"]
- McKittrick, Ross R. (2025) Extended Crop Yield Meta-analysis Data do not Support Upward SCC Revision. *Scientific Reports* 15 article 5575 [HYPERLINK "<https://www.nature.com/articles/s41598-025-90254-2>"]
- Mohaddes, Kamiar, Ryan Ng., Hashem Psaran, Mehdi Raissi and Jui-Chung Yang (2023) Climate change and economic activity: evidence from US states. *Oxford Open Economics* Vol 2 odac010 [HYPERLINK "<https://doi.org/10.1093/ooec/odac010>"]
- Moore, Frances C. and Delavane B. Diaz (2015) Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, 5(2):127–131, 2015. ISSN 1758-678X.
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. [HYPERLINK "<https://doi.org/10.1038/s41467-017-01792-x>"]
- Newell, Richard G., Brian C. Prest, and Steven E. Sexton (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, 108 [HYPERLINK "<https://doi.org/10.1016/j.jeem.2021.102445>"]
- Nordhaus, William (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517, 2006. ISSN 0027-8424.
- Nordhaus, William. (2018) Projections and Uncertainties About Climate Change in an Era of Minimal Climate Policies. *American Economic Journal: Economic Policy* August 2018, 10(3): 333-360. [HYPERLINK "<https://pubs.aeaweb.org/doi/pdfplus/10.1257/pol.20170046>"]

- Nordhaus, W. (1993) Optimal Greenhouse-Gas Reductions and Tax Policy in the "DICE" Model *American Economic Review* Vol. 83, No. 2, (Papers and Proceedings) pp.313-317.
- Palmer, T.N, A Döring and G Seregin (2014) The real butterfly effect. *Nonlinearity* 27(9) 10.1088/0951-7715/27/9/R123 [HYPERLINK "https://iopscience.iop.org/article/10.1088/0951-7715/27/9/R123/meta"]
- Pielke Jr., Roger (2018): Tracking progress on the economic costs of disasters under the indicators of the sustainable development goals, *Environmental Hazards*, DOI: 10.1080/17477891.2018.1540343
- Pielke Jr., Roger (2020) Economic ‘normalisation’ of disaster losses 1998–2020: a literature review and assessment,” *Environmental Hazards*, 2020, pp. 1-19
- Pielke Jr., Roger (2023) Global disaster losses: 1990-2023 Substack essay [HYPERLINK "https://rogerpielkejr.substack.com/p/global-disaster-losses1990-2023"]
- Resources for the Future (2025) “Social Cost of Carbon Explorer,” Resources for the Future website, accessed April 22, 2025, [HYPERLINK "https://www.rff.org/publications/data-tools/scc-explorer/"].
- Roe, Gerard H. and Yoram Bauman (2013) Climate Sensitivity: Should the climate tail wag the policy dog? *Climatic Change* (2013) 117:647–662 DOI 10.1007/s10584-012-0582-6
- Sandmo, Agnar (1975) “Optimal Taxation in the Presence of Externalities.” *Swedish Journal of Economics* 77 (1), 86–98.
- Schelling, Thomas C (1992) Some economics of global warming. *The American Economic Review*, 82 (1):1–14.
- Shen, Bo-Wen, Roger A Pielke Sr and Xubin Zeng (2023) The 50th Anniversary of the Metaphorical Butterfly Effect since Lorenz (1972): Multistability, Multiscale Predictability, and Sensitivity in Numerical Models. *Atmosphere* 2023 14(8) [HYPERLINK "https://doi.org/10.3390/atmos14081279"]
- Storm, S (2017) “How the Invisible Hand is Supposed to Adjust the Natural Thermostat: A Guide for the Perplexed.” *Science and Engineering Ethics* vol 23: 1307—1331.
- Thoung, Chris (2017) “Is It Time to Kill Off the Social Cost of Carbon?” Cambridge Econometrics Blog, September 14, 2017, [HYPERLINK "https://www.camecon.com/blog/time-kill-social-cost-carbon/"].
- Tol, Richard S.J. (1997) On the optimal control of carbon dioxide emissions: an application of FUND *Environmental Modeling and Assessment* 2: 151—163.
- Tol, Richard S.J. (2017). "The Private Benefit of Carbon and its Social Cost," Working Paper Series 0717, Department of Economics, University of Sussex Business School. [HYPERLINK "https://ideas.repec.org/p/sus/susewp/0717.html"]
- Tol, Richard S.J. (2024) A meta-analysis of the total economic impact of climate change. *Energy Policy* 185 113922 [HYPERLINK "https://doi.org/10.1016/j.enpol.2023.113922"]
- UK Department for Energy Security and Net Zero (2022). “Carbon Valuation.” GOV.UK, last updated April 4, 2022. [HYPERLINK "https://www.gov.uk/government/collections/carbon-valuation--2"].
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, “Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review”, EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, [HYPERLINK "https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf"] accessed February 28, 2024.
- Yang, Yimin, Fei Jia, and Haoran Li. Estimation of panel data models with mixed sampling frequencies (2023). *Oxford Bulletin of Economics and Statistics*, 85(3):514–544.
- Zhao, Xiaobing, Mason Gerety, and Nicolai V. Kuminoff (2018) Revisiting the temperature-economic growth relationship using global subnational data. *Journal of environmental management*, 223:537–544, 2018.

OUO – Official Use Only

12 GLOBAL CLIMATE IMPACTS OF U.S. EMISSIONS POLICIES

Chapter Summary

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

12.1 The scale problem

The emissions rates and atmospheric concentrations of criteria air contaminants are closely connected because their lifetimes are short and their concentrations are small; when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since emissions mix globally and the global carbon cycle is vast and slow. Any change in local CO₂ emissions today will have only a very small global effect, and only with a long delay.

Following the emission of a pulse (release) of CO₂ into the atmosphere only about 40 ± 15 percent of the extra CO₂ will have been sequestered after twenty years. That fraction rises to 75 ± 10 percent after a thousand years, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais *et al.*, 2013, pp.472-473). Consequently, any reduction in U.S. emissions would only modestly slow, but not prevent, the rise of global CO₂ concentration. And even if global emissions were to stop tomorrow, it would take decades or centuries to see a meaningful reduction in the global CO₂ concentration and hence human influences on the climate.

Reducing the atmospheric stock of CO₂ would require emissions to fall below the natural sequestration rate, assuming the entire increase is anthropogenic. Since that rate has been averaging about 50 percent of emissions in recent decades, a reduction of global emissions by 50 percent would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy was too difficult for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley, 1998). Lomborg (2016) estimated that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions will have negligible local effects, and only with a long delay. The practice of referring to unilateral U.S. reductions as “combating climate change” or “taking action on climate” therefore reflects a profound misunderstanding of the scale of the issue.

12.2 Case study: U.S. motor vehicle emissions

The scale problem can be illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. The 2009 Endangerment Finding therefore obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the U.S. public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing U.S. vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to the reduction in global emissions, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0 percent of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating *all* U.S. vehicle-based emissions would retard the accumulation of CO₂ in the atmosphere by a year or two over a century.

It would also reduce the overall warming trend by at most about 3 percent. For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends are determined to a precision of about ± 15 percent, so the impact of reducing the rate of global warming by eliminating U.S. vehicle CO₂ emissions would be far below the limits of measurability. Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, in contrast to the case of local air contaminants like particulates and ozone, even the most aggressive regulatory actions on GHG emissions from U.S. vehicles cannot be expected to remediate alleged climate dangers to the U.S. public on any measurable scale.

References

- Ciais, P., C. Sabine, G. Bala, L. Bopp, V. Brovkin, *et al.* (2013): Carbon and Other Biogeochemical Cycles. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, *et al.* (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- EPA (2024) *Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions 1990-2022*. Available online at [HYPERLINK "<https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockkey=P101AKR0.pdf>"]
- Energy Institute (2024) Statistical Review of World Energy. Available online at [HYPERLINK "<https://www.energyinst.org/statistical-review>"]
- Lomborg, Bjorn (2016) "Impact of Current Climate Proposals" *Global Policy* 7(1) 109–118. Available at <http://onlinelibrary.wiley.com/doi/10.1111/1758-5899.12295/full>.
- Wigley, T.M.L. (1998). "The Kyoto Protocol: CO₂, CH₄ and climate implications." *Geophysical Research Letters* 25(13), 2285-2288

GLOSSARY

2XCO₂: Doubling of the atmospheric carbon dioxide (CO₂), a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50 percent of the way to 2XCO₂ compared to 1800.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

ACRIM (Active Cavity Radiometer Irradiance Monitor) GAP: the gap in total solar irradiance data between 1989 and 1991 caused by a delay in the launch of a satellite-borne monitor in time to overlap and intercalibrate with the prior system.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The "opposite" of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

AMO: Atlantic Multidecadal Oscillation, a 60-year cycle of sea surface temperatures in the North Atlantic.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science and the others concerned with societal impacts and mitigation strategies. The most recent was AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CLIMATE CHANGE: A change in climate due to human influences, as opposed to climate variability which is natural in origin.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyse economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens of a country, including exports and imports, usually over one year.

GDP (Gross National Product): Total market value of all the domestically-produced final goods and services produced by the citizens of a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

OUO – Official Use Only

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PDO: Pacific Decadal Oscillation, a recurring ocean-atmosphere interaction centered over the Pacific basin associated with predominantly warm or cool patterns that influence the global climate.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP 6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TONNE: Metric ton.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

TSI (Total Solar Irradiance): The measure of the total amount of incident solar radiation per unit area, including all wavelengths of electromagnetic radiation, that reaches the Earth's atmosphere. Typically shown in units of watts per square meter (W/m²).

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

METADATA FOR FIGURES AND TABLES

Figure 2.1 Screen shot from Figure 3 of Zhu *et al.* 2016 [HYPERLINK "<https://www.nature.com/articles/nclimate3004>"]

Figure 2.2 Data replotted from Berner 2006 Figure 18, with annotation in red added by authors [HYPERLINK "<https://www.sciencedirect.com/science/article/pii/S0016703706002031>"]

Figure 2.3 Screen shot from Gerhart and Ward (2010) Figure 2 [HYPERLINK "<https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>"]

Figure 2.4 Screenshot from Copernicus Marine Services [HYPERLINK "https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description"]

Figure 2.5 Screen shot from AIMS (2023) Figures 2-4 [HYPERLINK "https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf"]

Figure 3.1.1 Screen shot of AR6 WGI Ch2 Fig 10

Figure 3.1.2 Screen shot of AR6 WGI Ch7 Fig 7-6

Figure 3.1.3 Author created figure. CO2 data source: [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]

Figure 3.2.1 Screen shot from Hausfather *et al.* (2019) Figure S4 [HYPERLINK "<https://doi.org/10.1029/2019GL085378>"]

Figure 3.2.2 Author created figure. Data source: Freidlingstein *et al.* (2024) [HYPERLINK "<https://essd.copernicus.org/preprints/essd-2024-519>"]
Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 3.2.3 Author-created using OLS trends, Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 3.2.4 Author-created using OLS trends, Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 4.1 Screen shot from Scafetta (2021) Figure 1 [HYPERLINK "<https://doi.org/10.3390/cli9110161>"]

Figure 5.1 Data source: [HYPERLINK "<https://climexp.knmi.nl/start.cgi>"]. Author-created figure. One ensemble member per model, yearly average temperatures are computed from the global monthly raw temperatures; 'range' is the warmest model temperature minus the coolest model temperature in each year; standard deviation computed across all 33 models' raw temperatures in each year.

Figure 5.2 Screen shot from Scafetta (2023) Figure 2 [HYPERLINK "<https://doi.org/10.1007/s00382-022-06493-w>"]

Figure 5.3 Author created figure. Data source: [HYPERLINK "<https://climexp.knmi.nl/start.cgi>"]. One SSP370 ensemble member per model. Linear OLS trends computed from global monthly temperature anomalies relative to 1981-2010.

Figure 5.4 Author created figure, based on Figure 3 of McKittrick and Christy (2020) [HYPERLINK "<https://doi.org/10.1029/2020EA001281>"]. Updated using same methods and data extended from 2014 to 2024, see McKittrick and Christy (2025) in chapter references.

Figure 5.6 Screen shot of IPCC AR5 Figure 10.SM1, with author annotations

Figure 5.7 Author created figure following Christy and McNider (2017) [HYPERLINK "<https://doi.org/10.1007/s13143-017-0070-z>"] with updated data available at [HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/ERA5_REANALYSES/"] and [HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/JRA3Q_REANALYSES/"] compiled here [HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/CWG25_Fig_5.7_Table_250627.xlsx"]

Figure 5.8 Screen shot from [HYPERLINK "https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"] (accessed May 27, 2025)

Figure 5.9 Screen shot from Rugenstein and Hakuba (2023) Figure 1 [HYPERLINK "<https://doi.org/10.1029/2022GL101802>"]

Figure 5.10 Author created figure. Data source [HYPERLINK "<https://climexp.knmi.nl/start.cgi>"]. OLS linear trends. One SSP370 ensemble member per model, averaged surface air temperatures for June through August over 31N to 49N latitude, 84W to 102W longitude. Observed temperature data for same months from NOAA/NCEI at <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series> for the 12 Corn Belt states averaged together.

Figure 6.1.1 Author replot of Figure 10 from Koutsoyiannis (2013) [HYPERLINK "<http://dx.doi.org/10.1080/02626667.2013.804626>"]

Figure 6.2.1 Screen shot of figure from Maue (2025) [HYPERLINK "<https://climatlas.com/tropical/>"]

Figure 6.2.2 Author created figure. Data from National Hurricane Center (2024) [HYPERLINK "<https://www.nhc.noaa.gov/climo/>"]

Figure 6.2.3 Author created figure. Data from NOAA HRD [HYPERLINK "https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html" \t "_new"]

Table 6.2.1 Author created table. Data from NOAA HRD [HYPERLINK "https://www.aoml.noaa.gov/hrd/hurdat/most_intense.html" \t "_new"]

Figure 6.3.1 Screen shot from NCA4 Figure 6.4

Figure 6.3.2 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.3 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.4 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.5 Author created figure Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.6 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.7 Screen shot from [HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"]

Box tables. Author created table. Data from McKittrick and Christy (2025)

Figure 6.4.1 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.2 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.3 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.4 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.5 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.5.1 Author created figure. Data source: [HYPERLINK "https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv"]

Figure 6.7.1 Author created figure. Data source: [HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"] accessed June 16, 2025. OLS trend line added.

Figure 6.8.1 Screen shot from Lizundia-Loiola *et al.* (2021) Figure 12.

Figure 6.8.2 Screenshot from Marlon *et al.* (2012) Figure 2 panel C. [HYPERLINK "https://www.pnas.org/doi/pdf/10.1073/pnas.1112839109"]

Figure 6.8.3 Author created Figure. Data 1926 to 2016: [HYPERLINK "https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html"]. Post-2017 [HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"] Accessed June 16, 2025.

Figure 7.1 Screenshot from [HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/"]

Table 7.1 Author created table. From Section 6.2 of [HYPERLINK "https://judithcurry.com/wp-content/uploads/2018/11/special-report-sea-level-rise-3.pdf"]

Figure 7.2 Screenshot from [HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290"] (downloaded 4/22/25)

Figure 7.3 Screenshot from

[HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450"]
(downloaded 4/22/2025)

Figure 7.4 Screenshot from

[HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724"]
(downloaded 4/22/25)

Figure 7.5 Screenshot from

[HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750"]
(downloaded 4/22/25)

Figure 7.6 Author created figure. Data from [HYPERLINK

"https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750"]

Figure 8.1 Screenshot from

[HYPERLINK "<https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf>"]

Figure 8.2 Screenshot from Hansen and Karecha (2025) Figure 1

[HYPERLINK "<https://www.columbia.edu/~jeh1/mailings/2025/CloudFeedback.13May2025.pdf>"]

Table 8.1 Screenshot of column 1 of Table 12.12 IPCC AR6 Working Group I report

Figure 9.1 Screenshot From Taylor and Schlenker (2021) Figure 1

[HYPERLINK "<https://www.nber.org/papers/w29320>"]

Figure 9.2 Screenshot from McKittrick (2025) Figure 1

[HYPERLINK "<https://www.nature.com/articles/s41598-025-90254-2>"]

Figure 10.1 Screenshot from Pielke (2024) [HYPERLINK "<https://www.nature.com/articles/s44304-024-00011-0>"] Figure 3.

Figure 10.2 Screenshot from Gasparini *et al.* (2015) Figure 2

[HYPERLINK "[http://dx.doi.org/10.1016/S0140-6736\(14\)62114-0](http://dx.doi.org/10.1016/S0140-6736(14)62114-0)"]

Figure 11.1 Screen shot from Pielke Jr (2023)

[HYPERLINK "<https://rogerpielkejr.substack.com/p/global-disaster-losses1990-2023>"]

Figure 11.2 Screenshot from CEA-OMB (2023) [HYPERLINK

"<https://bidenwhitehouse.archives.gov/wp-content/uploads/2023/03/CEA-OMB-White-Paper.pdf>"]
Figure 1.

ABOUT THE AUTHORS

John Christy, Ph.D. is the Distinguished Professor of Atmospheric and Earth Sciences and Alabama's State Climatologist at the University of Alabama in Huntsville. He has a B.A. (Mathematics) from CSU Fresno and an M.S. and Ph.D. (Atmospheric Sciences) from the University of Illinois in Urbana-Champaign. He is a Fellow of the American Meteorological Society and recipient of The NASA Medal for Exceptional Scientific Achievement for constructing, with Dr. Roy Spencer, the first global atmospheric temperature dataset from polar orbiting satellites. He served as Lead Author of the 3rd IPCC Assessment Report (2001), he coauthored the National Academy of Science expert report on Surface Temperature Reconstructions (2006), and he has served on the NOAA Climate Change Science Program, NASA's Earth Science Subcommittee, the National Research Council Space Studies Board and the EPA Science Advisory Board. In addition, Dr. Christy has given testimony in 20 Congressional Hearings.

Judith Curry, Ph.D. is Professor Emerita at the Georgia Institute of Technology, where she served as Chair of Earth and Atmospheric Sciences for 13 years. She is President and co-founder of Climate Forecast Applications Network (CFAN). Curry has a PhD in Geophysical Sciences from the University of Chicago. She has authored or coauthored 192 peer-reviewed papers in atmospheric and climate sciences, two textbooks, and most recently the book *Climate Uncertainty and Risk*. Curry is a Fellow of the American Meteorological Society, the American Association for the Advancement of Science, American Geophysical Union, and a Member of the American Academy of Sciences and Letters. She has served on several Science Steering Committees of the World Climate Research Program and also the DOE Biological & Environmental Research Advisory Committee, Earth Science Subcommittee of the NASA Advisory Council, and the NRC Space Studies Board and Climate Research Committee. Dr. Curry has given testimony in 13 Congressional Hearings.

The Honorable Steven E. Koonin, Ph.D. is the Edward Teller Senior Fellow at Stanford's Hoover Institution. He has served as Under Secretary for Science at the Department of Energy (2009-2011), as Chief Scientist for British Petroleum (2004-2009), and as a professor at Caltech (1975 – 2004, the last nine years as Vice President and Provost). Koonin is a member of the National Academy of Sciences and the JASON group of government advisors, as well as a Governor of Lawrence Livermore National Laboratory, having served in similar capacities for the Los Alamos, Sandia, Brookhaven, and Argonne National Laboratories. Other prior roles include a University Professor at New York University, a non-resident Senior Fellow at the American Enterprise Institute, and a Trustee of the Institute for Defense Analyses. Koonin has a BS in Physics from Caltech and a PhD in Theoretical Physics from Massachusetts Institute of Technology. He authored the 2021 bestseller *Unsettled: What Climate Science Tells Us, What It Doesn't, and Why It Matters*, the 1985 textbook *Computational Physics*, and some 200 peer-reviewed papers in physics and astrophysics, scientific computation, energy technology and policy, and climate science.

Ross McKittrick, Ph.D., is a Professor of Environmental Economics at the University of Guelph in Ontario, Canada. He holds a BA in economics from Queen's University, and an MA and Ph.D. in economics from the University of British Columbia. He has published widely in both economics and physical science journals on topics related to climate change, pollution and public policy. His book *Economic Analysis of Environmental Policy* was published by the University of Toronto Press in 2010. His background in applied statistics has led him to author or coauthor peer-reviewed publications across a wide range of topics in the physical sciences including paleoclimate reconstruction, malaria transmission, surface temperature measurement, climate attribution methodology and climate model evaluation. Professor McKittrick has made many invited academic presentations around the world, was an invited contributor to the 2006

OUO – Official Use Only

National Academy of Sciences report on Surface Temperature Reconstructions, has served as an expert reviewer for the last three IPCC Assessment Reports (Working Groups I and II) and has testified before the U.S. Congress and committees of the Canadian House of Commons and Senate.

Roy W. Spencer, Ph.D., is a Principal Research Scientist at the University of Alabama in Huntsville. He holds a BS in Atmospheric and Oceanic Science from the University of Michigan, and MS and PhD in Meteorology from the University of Wisconsin -Madison. Spencer's published research has focused on monitoring of weather processes and climate change from Earth-orbiting satellites, as well as using simple physical models for diagnosing climate sensitivity and climate feedbacks. As a NASA Senior Scientist for Climate Studies he served as the U.S. Science Team Leader for the Advanced Microwave Scanning Radiometer (AMSR-E) flying on the Aqua satellite, providing our most accurate global measurements of sea surface temperatures, sea ice, and several other features of the climate system. Along with Dr. John Christy, Spencer developed the first satellite-based technique for global temperature monitoring, for which they received NASA's Exceptional Scientific Achievement Medal and the American Meteorological Society's Special Award.

- Aldrin, M., M. Holden, P. Guttorp, R. B. Skeie, G. Myhre, and T. K. Berntsen, (2012): Bayesian estimation of climate sensitivity based on a simple climate model fitted to observations of hemispheric temperatures and global ocean heat content. *Environmetrics*, 23, 253-271. [HYPERLINK "<https://onlinelibrary.wiley.com/doi/full/10.1002/env.2140>"]
- Allen, M.R. and P.A. Stott (2003) Estimating Signal Amplitudes in Optimal Finger-Printing, Part I: Theory. *Climate Dynamics* 21:477—491. DOI 10.1007/s00382-003-0313-9
- Allen, M.R. and S.F..B. Tett (1999) Checking for model consistency in optimal fingerprinting. *Climate Dynamics* 15: 419–434 [HYPERLINK "<https://doi.org/10.1007/s003820050291>"].
- Arent, D.J., R.S.J. Tol, E. Faust, J.P. Hella, S. Kumar, K.M. Strzepek, F.L. Tóth, and D. Yan (2014) Key economic sectors and services. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 659-708.[HYPERLINK "https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap10_FINAL.pdf"]
- Balcombe, Kevin, Iain Fraser and Abhijit Sharma (2019) Is radiative forcing cointegrated with temperature? A further examination using a structural time series approach." *Management of Environmental Quality* 30(5) DOI 10.1108/MEQ-12-2018-021.
- Bareille, F. and R. Chakir (2023) The impact of climate change on agriculture: A repeat-Ricardian analysis. *Journal of Environmental Economics and Management* 119
- Barker, D. (2023) Temperature Shocks and Economic Growth: Comment on Dell, Jones, and Olken. *Econ Journal Watch* 20(2) 234-253 [HYPERLINK "<https://econjwatch.org/articles/temperature-shocks-and-economic-growth-comment-on-dell-jones-and-olken>"]
- Bates, J.R. (2016) Estimating climate sensitivity using two-zone energy balance models. *Earth and Space Science* 3, 207–225, doi:10.1002/2015EA000154. [HYPERLINK "<https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1002/2015EA000154>"]
- Beenstock, M., Y. Reingewertz and N. Paldor (2012). "Polynomial cointegration tests of anthropogenic impact on global warming." *Earth System Dynamics* 3:173-188 doi:10.5194/esd-3-173-2012
- Bengtsson, Lennart and Stephen E. Schwartz (2013) Determination of a lower bound on Earth's climate sensitivity. *Tellus B: Chemical and Physical Meteorology* 65(1) [HYPERLINK "<https://b.tellusjournals.se/articles/10.3402/tellusb.v65i0.21533>"]
- Berg, Kimberly, Chadwick C Curtis and Nelson Mark. (2021) GDP and temperature: Evidence on cross-country response heterogeneity. NBER Working Paper 31327 June 2023 [HYPERLINK "<http://www.nber.org/papers/w31327>"]
- Brown-Steiner, Benjamin (2024) What Really Does A Climate Model Do, 2024: [HYPERLINK "<https://earthathome.org/de/climate-modeling/what-really-does-a-climate-model-do>"] Online resource
- Burgess, Matthew et al (2021) Environmental Research Letters 16 014016 [HYPERLINK "<https://iopscience.iop.org/article/10.1088/1748-9326/abcdd2/meta>"]
- Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.
- Butler, Ethan E., Nathaniel D. Mueller and Peter Huybers (2018) Peculiarly pleasant weather for US maize. *Proceedings of the National Academy of Sciences* 115(47) 11935–11940 [HYPERLINK "<http://www.pnas.org/cgi/doi/10.1073/pnas.1808035115>"]
- Cannon, Alex (2024) The Impact of 'Hot Models' on a CMIP6 Ensemble Used by Climate Service Providers in Canada: Do Global Constraints Lead to Appreciable Differences in Regional Projections? *Journal of Climate* 37(6) pp. 2141–2154 [HYPERLINK "<https://journals.ametsoc.org/view/journals/clim/37/6/JCLI-D-23-0459.1.xml>"]

- Challinor, Andrew J., et al. A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* 4.4 (2014): 287.
- Chand et al. (2022) Declining tropical cyclone frequency under global warming. *Nature* 12 655—661. [HYPERLINK "<https://www.nature.com/articles/s41558-022-01388-4>"]
- Charney, J., Arakawa, A., Baker, D. J., Bolin, B., Dickenson, R. E., Goody, R. M., Leith, C. E., Stommel, H. M., and Wunsch, C. I. (1979) Carbon Dioxide and Climate: A scientific assessment, Tech. rep., National Academy of Sciences, Woods Hole, MA, <https://doi.org/10.17226/12181>, 34 pp., 1979.
- Chen, H, SX Chen and M Mu (2023) A statistical review on the optimal fingerprinting approach in climate change studies. *Climate Dynamics* 62:1439-1446 [HYPERLINK "<https://link.springer.com/article/10.1007/s00382-023-06975-5>"]
- Christy, J.R. and McNider, R.T. (2017). Satellite bulk tropospheric temperatures as a metric for climate sensitivity. *Asia-Pacific Journal of Atmospheric Science* 53(4) 511-518 DOI:10.1007/s13143-017-0070-z [HYPERLINK "<https://link.springer.com/article/10.1007/s13143-017-0070-z>"]
- Christy, JR. and R McNider (2017) Satellite Bulk Tropospheric Temperatures as a Metric for Climate Sensitivity. *Asia-Pacific Journal of Atmospheric Sciences* 53(4) 511—518. DOI:10.1007/s13143-017-0070-z
- Ciais, P., C. Sabine, G. Bala, L. Bopp, V. Brovkin, et al. (2013): Carbon and Other Biogeochemical Cycles. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- CO2Science.org (undated) Plant growth archive http://www.co2science.org/data/plant_growth/dry/dry_subject_b.php
- Connolly et al. (2019) Northern Hemisphere Snow-Cover Trends (1967–2018): A Comparison between Climate Models and Observations *Geosciences* 2019, 9(3), 135 [HYPERLINK "<https://www.mdpi.com/2076-3263/9/3/135>"]
- Crisp, David & Dolman, Han (A.J.) & Tanhua, Toste & Mckinley, Galen & Hauck, Judith & Bastos, Ana & Sitch, Stephen & Eggleston, Simon & Aich, Valentin. (2022). How Well Do We Understand the Land-Ocean-Atmosphere Carbon Cycle?. *Reviews of Geophysics*. 60. 10.1029/2021RG000736.
- Davidson, James E.H., David B. Stephenson and Alemtsehai A. Turasie (2015) Time series modeling of paleoclimate data. *Environmetrics* 27(1) pp. 55-65 [HYPERLINK "<https://doi.org/10.1002/env.2373>"]
- Dayaratna, Kevin and Ross McKittrick (2023) "Reply to comment on "climate sensitivity, agricultural productivity and the social cost of carbon in fund" by Philip Meyer" *Environmental Economics and Policy Studies* 2023 link.springer.com/article/10.1007/s10018-023-00364-2
- Dayaratna, Kevin, Ross McKittrick and David Kreutzer (2017) Empirically-Constrained Climate Sensitivity and the Social Cost of Carbon. *Climate Change Economics* April 2017 DOI: [HYPERLINK "<http://dx.doi.org/10.1142/S2010007817500063>"]
- Dayaratna, Kevin, Ross McKittrick and Patrick J. Michaels (2020) Climate Sensitivity, Agricultural Productivity and the Social Cost of Carbon in FUND. *Environmental Economics and Policy Studies* <https://doi.org/10.1007/s10018-020-00263-w>
- Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American economic journal: Macroeconomics*, 4(3):66–95, 2012. ISSN 1945-7707.
- Dergiades, T., R.K. Kaufmann and T. Panagiotidis (2016). Long-run changes in radiative forcing and surface temperature: The effect of human activity over the last five centuries. *Journal of Environmental Economics and Management* 76:67—85. [HYPERLINK "<https://www.sciencedirect.com/science/article/abs/pii/S0095069615000911>"]

- Deryng, D., Elliott, J., Folberth, C. *et al.* (2021) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* **6**, 786–790 (2016). [HYPERLINK "<https://doi.org/10.1038/nclimate2995>"]
- Doerr SH and Santin C. (2016) Global trends in wildfire and its impacts: perceptions versus realities in a changing world. *Philosophical Transactions of the Royal Society. B* 371: 20150345. [HYPERLINK "<http://dx.doi.org/10.1098/rstb.2015.0345>"]
- Forster, P., Storelvmo, T., Armour, K. C., Collins, W., Dufresne, J.-L., Frame, D., Lunt, D. J., Mauritsen, T., Palmer, M. D., Watanabe, M., Wild, M., and Zhang, H. (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V. *et al.* (eds.)], Cambridge University Press, 2021.
- Grandey, Benjamin, Zhi Yang Koh, and Dhrubajyoti Samanta, Benjamin Horton, Justin Dauwels, Lock Chew (2023). Monte Carlo Drift Correction – Quantifying the Drift Uncertainty of Global Climate Models. *Geoscientific Model Development*, 10.5194/egusphere-2022-1515.
- Greßer, Christina, Daniel Meierrieks, and David Stadelmann (2021) The link between regional temperature and regional incomes: econometric evidence with sub-national data. *Economic Policy*, 36(107):523–550, 2021.
- Hall, Alex and Syukuro Manabe (1997) The Role of Water Vapor Feedback in Unperturbed Climate Variability and Global Warming. *Journal of Climate* August 1999 Vol 12 pp. 2327—2346.
- Hausfather *et al.* (2019) "Evaluating the Performance of Past Climate Model Projections" *Geophysical Research Letters* 47(1) [HYPERLINK "<https://doi.org/10.1029/2019GL085378>"]
- Hausfather, Z. and G. Peters (2020) "Emissions – the 'business as usual' story is misleading" *Nature* 29 January 2020 [HYPERLINK "<https://www.nature.com/articles/d41586-020-00177-3>"]
- Hausfather, Z., K. Marvel, G. A. Schmidt, J. W. Nielsen-Gammon, and M. Zelinka (2022): Climate simulations: Recognize the 'hot model' problem. *Nature*, **605**, 26–29, [HYPERLINK "<https://doi.org/10.1038/d41586-022-01192-2>" \t "_blank"].
- Hegerl, G.C., F. W. Zwiers, P. Braconnot, N.P. Gillett, Y. Luo, J.A. Marengo Orsini, N. Nicholls, J.E. Penner and P.A. Stott, 2007: Understanding and Attributing Climate Change. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Hourdin, F, T Mauritsen, A Gettelman *et al.* (2017) The Art and Science of Climate Model Tuning. *Bulletin of the American Meteorological Society* 98, 589–602, [HYPERLINK "<https://doi.org/10.1175/BAMS-D-15-00135.1>"].
- [HYPERLINK "<https://doi.org/10.1002/env.2835>" 2023"].
- Hu, Shaowu, Yunxia Wang and Lianxin Yang (2021) Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: A meta-analysis of 20 years FACE studies, *Science of The Total Environment*, 764, 142797, [HYPERLINK "<https://doi.org/10.1016/j.scitotenv.2020.142797>"].
- IPCC Fifth Assessment Report (2013) Chapter 10 online Supplemental Material. Available online at [HYPERLINK "https://www.ipcc.ch/site/assets/uploads/2018/07/WGI_AR5_Chap.10_SM.pdf"]
- Irving, Damien. (2021). A Mass and Energy Conservation Analysis of Drift in the CMIP6 Ensemble. *Journal of Climate* 34(8) pp. 3157–3170. 10.22541/au.161618917.70147304/v1.
- Johansson D.J.A, Brian C. O'Neill, Claudia Tebaldi and Olle Häggström (2015) Equilibrium climate sensitivity in light of observations over the warming hiatus *Nature Climate Change* DOI: 10.1038/NCLIMATE2573 [HYPERLINK "<https://www.nature.com/articles/nclimate2573>"]
- Karl, T. R., S. J. Hassol, C. D. Miller, and W. L. Murray (2006). *Temperature Trends in the Lower Atmosphere: Steps for Understanding and Reconciling Differences*. Synthesis and Assessment

- Product. Climate Change Science Program and the Subcommittee on Global Change Research. <http://www.climatechange.gov/Library/sap/sap1-1/finalreport/sap1-1-final-all.pdf>. Accessed August 3 2010.
- Klotzbach PJ, Pielke Sr RA, Pielke Jr RA, Christy JR, McNider RT. 2009. An alternative explanation for differential temperature trends at the surface and in the lower troposphere. *Journal of Geophysical Research* **114**: D21102.
<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2009JD011841>
- Klotzbach, Phil (2025) Real Time Tropical Cyclone Statistics. [HYPERLINK "<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>"]
- Kogan, Feliz, Wei Guob and Wenze Yang (2020) "Near 40-year drought trend during 1981-2019 earth warming and food security" *Geomatics, Natural Hazards and Risk* Vol 11(1)
- Koop, G (2008) *Introduction to Econometrics*. Chichester: Wiley.
- Kossin, J et al. (2020) Global increase in major tropical cyclone exceedance probability over the past four decades *Proc Nat Acad Sci* 117 (22) 11975-11980 [HYPERLINK "<https://www.pnas.org/doi/10.1073/pnas.1920849117>"]
- Lee, Sukyoung, Peter R. Bannon, Mingyu Park & Joseph P. Clark (2024) Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint. *Asia-Pacific Journal of Atmospheric Sciences* Volume 60, pages 669–678 [HYPERLINK "<https://link.springer.com/article/10.1007/s13143-024-00373-5>"]
- Lewis, N (2022) Objectively combining climate sensitivity evidence. *Climate Dynamics* 60: 3139—3165 [HYPERLINK "<https://doi.org/10.1007/s00382-022-06468-x>"]
- Lewis, N. and J.A. Curry, C., (2015). The implications for climate sensitivity of AR5 forcing and heat uptake estimates. *Climate Dynamics*, 10.1007/s00382-014-2342-y. <https://search.proquest.com/openview/2f4994e4ab3a28571ecdff2edb3aeb13/>
- Lewis, N., (2013) An objective Bayesian, improved approach for applying optimal fingerprint techniques to estimate climate sensitivity. *Journal of Climate*, 26, 7414-7429. [HYPERLINK "<https://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00473.1>"]
- Lewis, N., and J. Curry, 2018: The impact of recent forcing and ocean heat uptake data on estimates of climate sensitivity. *Journal of Climate*. doi:10.1175/JCLI-D17-0667.1. [HYPERLINK "<https://journals.ametsoc.org/doi/10.1175/JCLI-D-17-0667.1>"]
- Lewis, N.: Objectively combining climate sensitivity evidence, *Climate Dynamics* 60, 3139-3165, [HYPERLINK "<https://doi.org/10.1007/s00382-022-06468-x>"], 2022.
- Lizundia-Loiola, Joshua, Gonzalo Oton, Rubén Ramo and Emilio Chuvieco (2020) A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data. *Remote Sensing of Environment* 236 [HYPERLINK "<https://www.sciencedirect.com/science/article/pii/S0034425719305127>"]
- Loehle, C., (2014). A minimal model for estimating climate sensitivity. *Ecological Modelling*, 276, 80-84 [HYPERLINK "<https://www.sciencedirect.com/science/article/pii/S0304380014000404>"]
- Lomborg, Bjorn (2016) "Impact of Current Climate Proposals" *Global Policy* 7(1) 109—118. Available at <http://onlinelibrary.wiley.com/doi/10.1111/1758-5899.12295/full>.
- Marlon, Jennifer, Patrick J Bartlein, Daniel G. Gavin et al. (2012) Long-term perspective on wildfires in the western USA *Proceedings of the National Academy of Sciences* February 14 2012 [HYPERLINK "<https://www.pnas.org/doi/pdf/10.1073/pnas.1112839109>"]
- Masters, T., 2014: Observational estimate of climate sensitivity from changes in the rate of ocean heat uptake and comparison to CMIP5 models. *Climate Dynamics*, 42, 2173-2181 DOI 10.1007/s00382-013-1770-4. [HYPERLINK "<https://link.springer.com/article/10.1007/s00382-013-1770-4>"]
- Maue, Ryan (2024) Climate Atlas [HYPERLINK "<https://climatlas.com/tropical/>"]
- McKittrick, R (2022a) Checking for model consistency in optimal fingerprinting: a comment. *Climate Dynamics* 58:405-511 [HYPERLINK "<https://doi.org/10.1007/s00382-021-05913-7>"]

- McKittrick, Ross and Joel Wood (2013) Co-fluctuation patterns of per capita carbon dioxide emissions: The role of energy markets. *Energy Economics* 39 pp. 1-12 [HYPERLINK "<https://www.sciencedirect.com/science/article/abs/pii/S0140988313000649>"]
- McKittrick, Ross and John R. Christy (2018) A Test of the Tropical 200-300mb Warming Rate in Climate Models. *Earth and Space Science* doi: 10.1029/2018EA000401. [HYPERLINK "<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018EA000401>"]
- McKittrick, Ross and John R. Christy (2020) Pervasive Warm Bias in CMIP6 Tropospheric Layers. *Earth and Space Science* Vol 7(9) September 2020 [HYPERLINK "<https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020EA001281>"]
- McKittrick, Ross R. (2022b) [HYPERLINK "<https://link.springer.com/article/10.1007/s00382-022-06315-z>" \t "_blank"]. *Climate Dynamics* 10.1007/s00382-022-06315-z
- McKittrick, Ross R. (2023) "TLS bias in climate fingerprinting regressions with heterogeneous noise variances and correlated explanatory variables" *Environmetrics*
- McKittrick, Ross R. (2025) Consistent Climate Fingerprinting. *Climate Dynamics* accepted for publication.
- McKittrick, Ross R. (2025) Extended crop yield meta-analysis data do not support upward SCC revision. *Nature Scientific Reports* 15 article 5575 [HYPERLINK "<https://www.nature.com/articles/s41598-025-90254-2>"]
- McKittrick, Ross R. and John Christy (2019) Assessing Changes in US Regional Precipitation on Multiple Time Scales *Journal of Hydrology* vol. 578 Nov 2019, [HYPERLINK "<https://doi.org/10.1016/j.jhydrol.2019.124074>"]
- McKittrick, Ross R., Mark Strazicich and Junsoo Lee (2012) "[HYPERLINK "<http://onlinelibrary.wiley.com/doi/10.1002/for.2248/abstract>" \t "_blank"]" *Journal of Forecasting*, Vol 32, Issue 5, pp 435-451 DOI: 10.1002/for.2248.
- McSweeney, Robert and Zeke Hausfather (2018) Q&A: How Do Climate Models Work? Online resource [HYPERLINK "<https://www.carbonbrief.org/qa-how-do-climate-models-work/>"]
- Mendelsohn, R., Morrison, W., Schlesinger, M. E., & Andronova, N. G. (2000). Country-specific market impacts of climate change. *Climatic Change*, 45(3-4), 553-569.
- Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, Sept 1994 753-771.
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>
- Moore, Frances C. and Delavane B. Diaz (2015) Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, 5(2):127–131, 2015. ISSN 1758-678X.
- National Academies of Sciences, Engineering, and Medicine. (2019). *Reproducibility and Replicability in Science*. Washington, DC: The National Academies Press. [HYPERLINK "<https://doi.org/10.17226/25303>"].
- Newell, Richard G., Brian C. Prest, and Steven E. Sexton (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, 108 [HYPERLINK "<https://doi.org/10.1016/j.jeem.2021.102445>"]
- Nordhaus, William (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517, 2006. ISSN 0027-8424.
- Nordhaus, William. (2018) Projections and Uncertainties About Climate Change in an Era of Minimal Climate Policies. *American Economic Journal: Economic Policy* August 2018, 10(3): 333-360. [HYPERLINK "<https://pubs.aeaweb.org/doi/pdfplus/10.1257/pol.20170046>"]
- Oton, Gonzalo, Joshua Lizundia-Loiola, M. Lucrecia Pettinari and Emilio Chuvieco (2021) Development of a consistent global long-term burned area product (1982–2018) based on AVHRR-LTDR data. *International Journal of Applied Earth Observation and Geoinformation* 103(1) [HYPERLINK "<https://www.sciencedirect.com/science/article/pii/S030324342100180X>"]

- Otto, A, Otto, FEL, Allen, MR, Boucher, O, Church, J, Hegerl, G, Forster, PM, Gillett, NP, Gregory, J, Johnson, GC, Knutti, R, Lohmann, U, Lewis, N, Marotzke, J, Stevens, B, Myhre, G and Shindell, D (2013) Energy budget constraints on climate response. *Nature Geoscience*, 6, 415–416. [HYPERLINK "<https://www.nature.com/articles/ngeo1836>"]
- Parks, Sean, Christopher Guiterman, Ellis Margolis et al. (2025) A fire deficit persists across diverse North American forests despite recent increases in area burned. *Nature Communications* 16 [HYPERLINK "<https://www.nature.com/articles/s41467-025-56333-8>"]
- Philipona, R. et al., 2018: Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming. *Journal of Geophysical Research: Atmospheres*, 123(22), 12509–512522, doi:10.1029/2018jd028901. [HYPERLINK "<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018JD028901>"]
- Pielke, Roger and Ritchie, Justin (2020) "Systemic Misuse of Scenarios in Climate Research and Assessment" Social Sciences Research Network April 2020, available at: [HYPERLINK "<https://ssrn.com/abstract=3581777>"]
- Pirtle, Zachary, Ryan Meyer and Hamilton, Andrew. (2010). What does it mean when climate models agree? A case for assessing independence among general circulation models. *Environmental Science & Policy - ENVIRON SCI POLICY*. 13. 351-361. 10.1016/j.envsci.2010.04.004.
- Ranasinghe, Roshanka & Ruane, Alex & Vautard, Robert & Arnell, Nigel & Coppola, Erika & Cruz, Faye & Dessai, Suraje & Islam, Akm & Rahimi, Mohammad & Ruiz Carrascal, Daniel & Sillmann, Jana & Sylla, Mouhamadou & Tebaldi, Claudia & Wang, Wen & Rashyd, Zaaboul. (2021). *IPCC Sixth Assessment Report Working Group I Chapter 12: Climate change information for regional impact and for risk assessment*.
- Razzak, Weshah A. (2022). "The Econometrics of Global Warming," *Journal of Economics and Econometrics*, vol. 65(2), pages 13-47.
- Resources for the Future (RFF) (2025). Global Energy Outlook online reference tool [HYPERLINK "<https://www.rff.org/publications/data-tools/global-energy-outlook/>"] accessed April 18, 2025.
- Ring, M.J., D. Lindner, E.F. Cross and M. E. Schlesinger (2012) Causes of the Global Warming Observed since the 19th Century. *Atmospheric and Climate Sciences*, 2, 401-415. [HYPERLINK "https://file.scirp.org/pdf/ACS20120400002_59142760.pdf"]
- Ritchie, Hannah Pablo Rosado, and Max Roser (2024) - "CO₂ emissions by fuel" Published online in 2020 at OurWorldinData.org, updated 2024. Retrieved from: '<https://ourworldindata.org/emissions-by-fuel>' [Online Resource]
- Roe GH, Baker MB (2007) Why is climate sensitivity so unpredictable? *Science* 318:629–632
- Rutgers University Snow Lab (undated) [HYPERLINK "<http://climate.rutgers.edu/snowcover/index.php>"]
- Scaffeta, N (2023) CMIP6 GCM ensemble members versus global surface temperatures. *Climate Dynamics* 60, 3091–3120 (2023). [HYPERLINK "<https://doi.org/10.1007/s00382-022-06493-w>"]
- Schelling, Thomas C (1992) Some economics of global warming. *The American Economic Review*, 82 (1):1–14.
- Schwartz, Stephen E., Robert J. Charlson and Henning Rodhe (2007) Quantifying climate change — too rosy a picture? *Nature Reports-Climate Change* Vol 2 pp. 23-24.
- Seager, R., Cane, M., Henderson, N., Lee, D. E., Abernathey, R., and Zhang, H. (2019): Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases, *Nat. Clim. Change*, 9, 517-522, <https://doi.org/10.1038/s41558-019-0505-x>, 2019
- Sen Gupta, Alexander & Jourdain, Nicolas & Brown, Jaclyn & Monselesan, Didier. (2013). Climate drift in the CMIP5 models. *Journal of Climate*. 26. 8597-8615. 10.1175/JCLI-D-12-00521.1.

- Shaviv, Nir J., Henrik Svensmark and Jan Veizer (2023) *Annals of the New York Academy of Sciences* 1519:7—19. [[HYPERLINK "https://nyaspubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1111/nyas.14920"](https://nyaspubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1111/nyas.14920)]
- Sherwood, S. C., and Forest, C. E.: (2024) Opinion: Can uncertainty in climate sensitivity be narrowed further?, *Atmospheric Chemistry and Physics*, 24, 2679-2686, [[HYPERLINK "https://doi.org/10.5194/acp-24-2679-2024"](https://doi.org/10.5194/acp-24-2679-2024)].
- Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., Hegerl, G., Klein, S. A., Marvel, K. D., Rohling, E. J., Watanabe, M., Andrews, T., Braconnot, P., Bretherton, C. S., Foster, G. L., Hausfather, Z., Heydt, A. S., Knutti, R., Mauritsen, T., Norris, J. R., Proistosescu, C., Rugenstein, M., Schmidt, G. A., Tokarska, K. B., and Zelinka, M. D. (2020) An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence, *Review of Geophysics*, 58, [[HYPERLINK "https://doi.org/10.1029/2019RG000678"](https://doi.org/10.1029/2019RG000678)].
- Simpson, I et al. (2024) Observed humidity trends in dry regions contradict climate models. *Proceedings of the National Academy of Sciences* 2024 Vol. 121 No. 1 e2302480120 [[HYPERLINK "https://www.pnas.org/doi/10.1073/pnas.2302480120"](https://www.pnas.org/doi/10.1073/pnas.2302480120)]
- Skeie, R.B., T. Berntsen, M. Aldrin, M. Holden, and G. Myhre. A lower and more constrained estimate of climate sensitivity using updated observations and detailed radiative forcing time series (2014) *Earth System Dynamics* 5, 139–175, 2014 doi:10.5194/esd-5-139-2014. <https://search.proquest.com/openview/05f113e95581027c9a9f0f0a2a1551ac/>
- Spencer, Roy (2024) Global Warming: Observations vs. Climate Models. Heritage Foundation January 2024 [[HYPERLINK "https://www.heritage.org/environment/report/global-warming-observations-vs-climate-models"](https://www.heritage.org/environment/report/global-warming-observations-vs-climate-models)]
- Spencer, Roy W. and John R. Christy (2024) Effective climate sensitivity distributions from a 1D model of global ocean and land temperature trends, 1970–2021 *Theoretical and Applied Climatology* 155 pp. 299-308. [[HYPERLINK "https://link.springer.com/article/10.1007/s00704-023-04634-7"](https://link.springer.com/article/10.1007/s00704-023-04634-7)]
- Stansfield et al. (2020) “Changes in Precipitation From North Atlantic Tropical Cyclones Under RCP Scenarios in the Variable-Resolution Community Atmosphere Model” *Geophys. Res. Letters* [[HYPERLINK "https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2019GL086930"](https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2019GL086930)]
- Stern, D and R. Kaufmann (2000) “Detecting a global warming signal in hemispheric temperature series: A structural time series analysis.” *Climatic Change* 47:411-438.
- Storm, S (2017) “How the Invisible Hand is Supposed to Adjust the Natural Thermostat: A Guide for the Perplexed.” *Science and Engineering Ethics* vol 23: 1307—1331.
- Taylor, Charles and Wolfram Schlenker (2023) Environmental drivers of agricultural productivity growth: CO2 fertilization of US field crops. National Bureau of Economic Research Working paper 29320, [[HYPERLINK "http://www.nber.org/paper/w29320"](http://www.nber.org/paper/w29320)]
- Tol, Richard (2002) “Estimates of the Damage Costs of Climate Change” *Environmental and Resource Economics* 21:47—73
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, “Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review”, EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, [[HYPERLINK "https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf"](https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf)]
- Vogelsang, T and N. Nawaz (2016) “Estimation and Inference of Linear Trend Slope Ratios With an Application to Global Temperature Data.” *Journal of Time Series Analysis* doi.org/10.1111/jtsa.12209 [[HYPERLINK "https://onlinelibrary.wiley.com/doi/abs/10.1111/jtsa.12209"](https://onlinelibrary.wiley.com/doi/abs/10.1111/jtsa.12209)]

- Wehner, M.F., J.R. Arnold, T. Knutson, K.E. Kunkel, and A.N. LeGrande, 2017: Droughts, floods, and wildfires. In: *Climate Science Special Report: Fourth National Climate Assessment, Volume I* [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 231-256 doi: 10.7930/J0CJ8BNN.
- Wigley, T.M.L. (1998). "The Kyoto Protocol: CO₂, CH₄ and climate implications." *Geophysical Research Letters* 25(13), 2285-2288
- Yang, Yimin, Fei Jia, and Haoran Li. Estimation of panel data models with mixed sampling frequencies (2023). *Oxford Bulletin of Economics and Statistics*, 85(3):514–544.
- Zhao, Xiaobing, Mason Gerety, and Nicolai V. Kuminoff (2018) Revisiting the temperature-economic growth relationship using global subnational data. *Journal of environmental management*, 223:537–544, 2018.

- Aldrin, M., M. Holden, P. Guttorp, R. B. Skeie, G. Myhre, and T. K. Berntsen, (2012): Bayesian estimation of climate sensitivity based on a simple climate model fitted to observations of hemispheric temperatures and global ocean heat content. *Environmetrics*, 23, 253-271. <https://onlinelibrary.wiley.com/doi/full/10.1002/env.2140>
- Allen, M.R. and P.A. Stott (2003) Estimating Signal Amplitudes in Optimal Finger-Printing, Part I: Theory. *Climate Dynamics* 21:477—491. DOI 10.1007/s00382-003-0313-9
- Allen, M.R. and S.F..B. Tett (1999) Checking for model consistency in optimal fingerprinting. *Climate Dynamics* 15: 419–434 <https://doi.org/10.1007/s003820050291>.
- Arent, D.J., R.S.J. Tol, E. Faust, J.P. Hella, S. Kumar, K.M. Strzepek, F.L. Tóth, and D. Yan (2014) Key economic sectors and services. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 659-708.https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap10_FINAL.pdf
- Balcombe, Kevin, Iain Fraser and Abhijit Sharma (2019) Is radiative forcing cointegrated with temperature? A further examination using a structural time series approach." *Management of Environmental Quality* 30(5) DOI 10.1108/MEQ-12-2018-021.
- Bareille, F. and R. Chakir (2023) The impact of climate change on agriculture: A repeat-Ricardian analysis. *Journal of Environmental Economics and Management* 119
- Barker, D. (2023) Temperature Shocks and Economic Growth: Comment on Dell, Jones, and Olken. *Econ Journal Watch* 20(2) 234-253 <https://econjwatch.org/articles/temperature-shocks-and-economic-growth-comment-on-dell-jones-and-olken>
- Bates, J.R. (2016) Estimating climate sensitivity using two-zone energy balance models. *Earth and Space Science* 3, 207–225, doi:10.1002/2015EA000154. <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1002/2015EA000154>
- Beenstock, M., Y. Reingewertz and N. Paldor (2012). "Polynomial cointegration tests of anthropogenic impact on global warming." *Earth System Dynamics* 3:173-188 doi:10.5194/esd-3-173-2012
- Bengtsson, Lennart and Stephen E. Schwartz (2013) Determination of a lower bound on Earth's climate sensitivity. *Tellus B: Chemical and Physical Meteorology* 65(1) <https://b.tellusjournals.se/articles/10.3402/tellusb.v65i0.21533>
- Berg, Kimberly, Chadwick C Curtis and Nelson Mark. (2021) GDP and temperature: Evidence on cross-country response heterogeneity. NBER Working Paper 31327 June 2023 <http://www.nber.org/papers/w31327>
- Brown-Steiner, Benjamin (2024) What Really Does A Climate Model Do, 2024: <https://earthathome.org/de/climate-modeling/what-really-does-a-climate-model-do> Online resource
- Burgess, Matthew et al (2021) Environmental Research Letters 16 014016 <https://iopscience.iop.org/article/10.1088/1748-9326/abcdd2/meta>
- Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.
- Butler, Ethan E., Nathaniel D. Mueller and Peter Huybers (2018) Peculiarly pleasant weather for US maize. *Proceedings of the National Academy of Sciences* 115(47) 11935–11940 www.pnas.org/cgi/doi/10.1073/pnas.1808035115
- Cannon, Alex (2024) The Impact of 'Hot Models' on a CMIP6 Ensemble Used by Climate Service Providers in Canada: Do Global Constraints Lead to Appreciable Differences in Regional Projections? *Journal of Climate* 37(6) pp. 2141–2154 <https://journals.ametsoc.org/view/journals/clim/37/6/JCLI-D-23-0459.1.xml>

- Challinor, Andrew J., et al. A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* 4.4 (2014): 287.
- Chand et al. (2022) Declining tropical cyclone frequency under global warming. *Nature* 12 655—661. <https://www.nature.com/articles/s41558-022-01388-4>
- Charney, J., Arakawa, A., Baker, D. J., Bolin, B., Dickenson, R. E., Goody, R. M., Leith, C. E., Stommel, H. M., and Wunsch, C. I. (1979) Carbon Dioxide and Climate: A scientific assessment, Tech. rep., National Academy of Sciences, Woods Hole, MA, <https://doi.org/10.17226/12181>, 34 pp., 1979.
- Chen, H, SX Chen and M Mu (2023) A statistical review on the optimal fingerprinting approach in climate change studies. *Climate Dynamics* 62:1439-1446 <https://link.springer.com/article/10.1007/s00382-023-06975-5>
- Christy, J.R. and McNider, R.T. (2017). Satellite bulk tropospheric temperatures as a metric for climate sensitivity. *Asia-Pacific Journal of Atmospheric Science* 53(4) 511-518 DOI:10.1007/s13143-017-0070-z <https://link.springer.com/article/10.1007/s13143-017-0070-z>
- Christy, JR. and R McNider (2017) Satellite Bulk Tropospheric Temperatures as a Metric for Climate Sensitivity. *Asia-Pacific Journal of Atmospheric Sciences* 53(4) 511—518. DOI:10.1007/s13143-017-0070-z
- Ciais, P., C. Sabine, G. Bala, L. Bopp, V. Brovkin, et al. (2013): Carbon and Other Biogeochemical Cycles. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- CO2Science.org (undated) Plant growth archive http://www.co2science.org/data/plant_growth/dry/dry_subject_b.php
- Connolly et al. (2019) Northern Hemisphere Snow-Cover Trends (1967–2018): A Comparison between Climate Models and Observations *Geosciences* 2019, 9(3), 135 <https://www.mdpi.com/2076-3263/9/3/135>
- Crisp, David & Dolman, Han (A.J.) & Tanhua, Toste & Mckinley, Galen & Hauck, Judith & Bastos, Ana & Sitch, Stephen & Eggleston, Simon & Aich, Valentin. (2022). How Well Do We Understand the Land-Ocean-Atmosphere Carbon Cycle?. *Reviews of Geophysics*. 60. 10.1029/2021RG000736.
- Davidson, James E.H., David B. Stephenson and Alemtsehai A. Turasie (2015) Time series modeling of paleoclimate data. *Environmetrics* 27(1) pp. 55-65 <https://doi.org/10.1002/env.2373>
- Dayaratna, Kevin and Ross McKittrick (2023) "Reply to comment on "climate sensitivity, agricultural productivity and the social cost of carbon in fund" by Philip Meyer" *Environmental Economics and Policy Studies* 2023 link.springer.com/article/10.1007/s10018-023-00364-2
- Dayaratna, Kevin, Ross McKittrick and David Kreutzer (2017) Empirically-Constrained Climate Sensitivity and the Social Cost of Carbon. *Climate Change Economics* April 2017 DOI: <http://dx.doi.org/10.1142/S2010007817500063>
- Dayaratna, Kevin, Ross McKittrick and Patrick J. Michaels (2020) Climate Sensitivity, Agricultural Productivity and the Social Cost of Carbon in FUND. *Environmental Economics and Policy Studies* <https://doi.org/10.1007/s10018-020-00263-w>
- Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American economic journal: Macroeconomics*, 4(3):66-95, 2012. ISSN 1945-7707.
- Dergiades, T., R.K. Kaufmann and T. Panagiotidis (2016). Long-run changes in radiative forcing and surface temperature: The effect of human activity over the last five centuries. *Journal of Environmental Economics and Management* 76:67—85. <https://www.sciencedirect.com/science/article/abs/pii/S0095069615000911>

- Deryng, D., Elliott, J., Folberth, C. *et al.* (2021) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* **6**, 786–790 (2016). <https://doi.org/10.1038/nclimate2995>
- Doerr SH and Santin C. (2016) Global trends in wildfire and its impacts: perceptions versus realities in a changing world. *Philosophical Transactions of the Royal Society. B* 371: 20150345. <http://dx.doi.org/10.1098/rstb.2015.0345>
- Forster, P., Storelvmo, T., Armour, K. C., Collins, W., Dufresne, J-L., Frame, D., Lunt, D. J., Mauritsen, T., Palmer, M. D., Watanabe, M., Wild, M., and Zhang, H. (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V. et al. (eds.)], Cambridge University Press, 2021.
- Grandey, Benjamin, Zhi Yang Koh, and Dhrubajyoti Samanta, Benjamin Horton, Justin Dauwels, Lock Chew (2023). Monte Carlo Drift Correction – Quantifying the Drift Uncertainty of Global Climate Models. *Geoscientific Model Development*, 10.5194/egusphere-2022-1515.
- Greßer, Christina, Daniel Meierrieks, and David Stadelmann (2021) The link between regional temperature and regional incomes: econometric evidence with sub-national data. *Economic Policy*, 36(107):523–550, 2021.
- Hall, Alex and Syukuro Manabe (1997) The Role of Water Vapor Feedback in Unperturbed Climate Variability and Global Warming. *Journal of Climate* August 1999 Vol 12 pp. 2327—2346.
- Hausfather et al. (2019) “Evaluating the Performance of Past Climate Model Projections” *Geophysical Research Letters* 47(1) <https://doi.org/10.1029/2019GL085378>
- Hausfather, Z. and G. Peters (2020) “Emissions – the ‘business as usual’ story is misleading” *Nature* 29 January 2020 <https://www.nature.com/articles/d41586-020-00177-3>
- Hausfather, Z., K. Marvel, G. A. Schmidt, J. W. Nielsen-Gammon, and M. Zelinka (2022): Climate simulations: Recognize the ‘hot model’ problem. *Nature*, **605**, 26–29, <https://doi.org/10.1038/d41586-022-01192-2>.
- Hegerl, G.C., F. W. Zwiers, P. Braconnot, N.P. Gillett, Y. Luo, J.A. Marengo Orsini, N. Nicholls, J.E. Penner and P.A. Stott, 2007: Understanding and Attributing Climate Change. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Hourdin, F, T Mauritsen, A Gettelman et al. (2017) The Art and Science of Climate Model Tuning. *Bulletin of the American Meteorological Society* 98, 589–602, <https://doi.org/10.1175/BAMS-D-15-00135.1>. <https://doi.org/10.1002/env.2835> 2023.
- Hu, Shaowu, Yunxia Wang and Lianxin Yang (2021) Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: A meta-analysis of 20 years FACE studies, *Science of The Total Environment*, 764, 142797, <https://doi.org/10.1016/j.scitotenv.2020.142797>.
- IPCC Fifth Assessment Report (2013) Chapter 10 online Supplemental Material. Available online at https://www.ipcc.ch/site/assets/uploads/2018/07/WGI_AR5_Chap.10_SM.pdf
- Irving, Damien. (2021). A Mass and Energy Conservation Analysis of Drift in the CMIP6 Ensemble. *Journal of Climate* 34(8) pp. 3157-3170. 10.22541/au.161618917.70147304/v1.
- Johansson D.J.A, Brian C. O'Neill, Claudia Tebaldi and Olle Häggström (2015) Equilibrium climate sensitivity in light of observations over the warming hiatus *Nature Climate Change* DOI: 10.1038/NCLIMATE2573 <https://www.nature.com/articles/nclimate2573>
- Karl, T. R., S. J. Hassol, C. D. Miller, and W. L. Murray (2006). *Temperature Trends in the Lower Atmosphere: Steps for Understanding and Reconciling Differences*. Synthesis and Assessment Product. Climate Change Science Program and the Subcommittee on Global Change Research.

- <http://www.climate-science.gov/Library/sap/sap1-1/finalreport/sap1-1-final-all.pdf>. Accessed August 3 2010.
- Klotzbach PJ, Pielke Sr RA, Pielke Jr RA, Christy JR, McNider RT. 2009. An alternative explanation for differential temperature trends at the surface and in the lower troposphere. *Journal of Geophysical Research* **114**: D21102.
<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2009JD011841>
- Klotzbach, Phil (2025) Real Time Tropical Cyclone Statistics.
<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>
- Kogan, Feliz, Wei Guob and Wenze Yang (2020) "Near 40-year drought trend during 1981-2019 earth warming and food security" *Geomatics, Natural Hazards and Risk* Vol 11(1)
- Koop, G (2008) *Introduction to Econometrics*. Chichester: Wiley.
- Kossin, J et al. (2020) Global increase in major tropical cyclone exceedance probability over the past four decades *Proc Nat Acad Sci* **117** (22) 11975-11980
<https://www.pnas.org/doi/10.1073/pnas.1920849117>
- Lee, Sukyoung, Peter R. Bannon, Mingyu Park & Joseph P. Clark (2024) Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint. *Asia-Pacific Journal of Atmospheric Sciences* Volume 60, pages 669–678 <https://link.springer.com/article/10.1007/s13143-024-00373-5>
- Lewis, N (2022) Objectively combining climate sensitivity evidence. *Climate Dynamics* **60**: 3139—3165 <https://doi.org/10.1007/s00382-022-06468-x>
- Lewis, N. and J.A. Curry, C., (2015). The implications for climate sensitivity of AR5 forcing and heat uptake estimates. *Climate Dynamics*, 10.1007/s00382-014-2342-y.
<https://search.proquest.com/openview/2f4994e4ab3a28571ecdff2edb3aeb13/>
- Lewis, N., (2013) An objective Bayesian, improved approach for applying optimal fingerprint techniques to estimate climate sensitivity. *Journal of Climate*, **26**, 7414-7429.
<https://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00473.1>
- Lewis, N., and J. Curry, 2018: The impact of recent forcing and ocean heat uptake data on estimates of climate sensitivity. *Journal of Climate*. doi:10.1175/JCLI-D17-0667.1.
<https://journals.ametsoc.org/doi/10.1175/JCLI-D-17-0667.1>
- Lewis, N.: Objectively combining climate sensitivity evidence, *Climate Dynamics* **60**, 3139-3165, <https://doi.org/10.1007/s00382-022-06468-x>, 2022.
- Lizundia-Loiola, Joshua, Gonzalo Oton, Rubén Ramo and Emilio Chuvieco (2020) A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data. *Remote Sensing of Environment* **236**
<https://www.sciencedirect.com/science/article/pii/S0034425719305127>
- Loehle, C., (2014). A minimal model for estimating climate sensitivity. *Ecological Modelling*, **276**, 80-84 <https://www.sciencedirect.com/science/article/pii/S0304380014000404>
- Lomborg, Bjorn (2016) "Impact of Current Climate Proposals" *Global Policy* **7**(1) 109—118. Available at <http://onlinelibrary.wiley.com/doi/10.1111/1758-5899.12295/full>.
- Marlon, Jennifer, Patrick J Bartlein, Daniel G. Gavin et al. (2012) Long-term perspective on wildfires in the western USA *Proceedings of the National Academy of Sciences* February 14 2012
<https://www.pnas.org/doi/pdf/10.1073/pnas.1112839109>
- Masters, T., 2014: Observational estimate of climate sensitivity from changes in the rate of ocean heat uptake and comparison to CMIP5 models. *Climate Dynamics*, **42**, 2173-2181 DOI 10.1007/s00382-013-1770-4. <https://link.springer.com/article/10.1007/s00382-013-1770-4>
- Maue, Ryan (2024) Climate Atlas <https://climatlas.com/tropical/>
- McKittrick, R (2022a) Checking for model consistency in optimal fingerprinting: a comment. *Climate Dynamics* **58**:405-511 <https://doi.org/10.1007/s00382-021-05913-7>
- McKittrick, Ross and Joel Wood (2013) Co-fluctuation patterns of per capita carbon dioxide emissions: The role of energy markets. *Energy Economics* **39** pp. 1-12
<https://www.sciencedirect.com/science/article/abs/pii/S0140988313000649>

- McKittrick, Ross and John R. Christy (2018) A Test of the Tropical 200-300mb Warming Rate in Climate Models. *Earth and Space Science* doi: 10.1029/2018EA000401. <https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018EA000401>
- McKittrick, Ross and John R. Christy (2020) Pervasive Warm Bias in CMIP6 Tropospheric Layers. *Earth and Space Science* Vol 7(9) September 2020 <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020EA001281>
- McKittrick, Ross R (2022b) On the choice of TLS versus OLS in climate signal detection regression. *Climate Dynamics* 10.1007/s00382-022-06315-z
- McKittrick, Ross R. (2023) "TLS bias in climate fingerprinting regressions with heterogeneous noise variances and correlated explanatory variables" *Environmetrics*
- McKittrick, Ross R. (2025) Consistent Climate Fingerprinting. *Climate Dynamics* accepted for publication.
- McKittrick, Ross R. (2025) Extended crop yield meta-analysis data do not support upward SCC revision. *Nature Scientific Reports* 15 article 5575 <https://www.nature.com/articles/s41598-025-90254-2>
- McKittrick, Ross R. and John Christy (2019) Assessing Changes in US Regional Precipitation on Multiple Time Scales *Journal of Hydrology* vol. 578 Nov 2019, <https://doi.org/10.1016/j.jhydrol.2019.124074>
- McKittrick, Ross R., Mark Strazicich and Junsoo Lee (2012) "Long-Term Forecasting of Global Carbon Dioxide Emissions: Reducing Uncertainties Using a Per-Capita Approach." *Journal of Forecasting*, Vol 32, Issue 5, pp 435-451 DOI: 10.1002/for.2248.
- McSweeney, Robert and Zeke Hausfather (2018) Q&A: How Do Climate Models Work? Online resource <https://www.carbonbrief.org/qa-how-do-climate-models-work/>
- Mendelsohn, R., Morrison, W., Schlesinger, M. E., & Andronova, N. G. (2000). Country-specific market impacts of climate change. *Climatic Change*, 45(3-4), 553-569.
- Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, Sept 1994 753-771.
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>
- Moore, Frances C. and Delavane B. Diaz (2015) Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, 5(2):127–131, 2015. ISSN 1758-678X.
- National Academies of Sciences, Engineering, and Medicine. (2019). *Reproducibility and Replicability in Science*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/25303>.
- Newell, Richard G., Brian C. Prest, and Steven E. Sexton (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, 108 <https://doi.org/10.1016/j.jeem.2021.102445>
- Nordhaus, William (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517, 2006. ISSN 0027-8424.
- Nordhaus, William. (2018) Projections and Uncertainties About Climate Change in an Era of Minimal Climate Policies. *American Economic Journal: Economic Policy* August 2018, 10(3): 333-360. <https://pubs.aeaweb.org/doi/pdfplus/10.1257/pol.20170046>
- Oton, Gonzalo, Joshua Lizundia-Loiola, M. Lucrecia Pettinari and Emilio Chuvieco (2021) Development of a consistent global long-term burned area product (1982–2018) based on AVHRR-LTDR data. *International Journal of Applied Earth Observation and Geoinformation* 103(1) <https://www.sciencedirect.com/science/article/pii/S030324342100180X>
- Otto, A, Otto, FEL, Allen, MR, Boucher, O, Church, J, Hegerl, G, Forster, PM, Gillett, NP, Gregory, J, Johnson, GC, Knutti, R, Lohmann, U, Lewis, N, Marotzke, J, Stevens, B, Myhre, G and Shindell, D (2013) Energy budget constraints on climate response. *Nature Geoscience*, 6, 415–416. <https://www.nature.com/articles/ngeo1836>

- Parks, Sean, Christopher Guiterman, Ellis Margolis et al. (2025) A fire deficit persists across diverse North American forests despite recent increases in area burned. *Nature Communications* 16 <https://www.nature.com/articles/s41467-025-56333-8>
- Philipona, R. et al., 2018: Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming. *Journal of Geophysical Research: Atmospheres*, 123(22), 12509–512522, doi:10.1029/2018jd028901. <https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018JD028901>
- Pielke, Roger and Ritchie, Justin (2020) "Systemic Misuse of Scenarios in Climate Research and Assessment" Social Sciences Research Network April 2020, available at: <https://ssrn.com/abstract=3581777>
- Pirtle, Zachary, Ryan Meyer and Hamilton, Andrew. (2010). What does it mean when climate models agree? A case for assessing independence among general circulation models. *Environmental Science & Policy - ENVIRON SCI POLICY*. 13. 351-361. 10.1016/j.envsci.2010.04.004.
- Ranasinghe, Roshanka & Ruane, Alex & Vautard, Robert & Arnell, Nigel & Coppola, Erika & Cruz, Faye & Dessai, Suraje & Islam, Akm & Rahimi, Mohammad & Ruiz Carrascal, Daniel & Sillmann, Jana & Sylla, Mouhamadou & Tebaldi, Claudia & Wang, Wen & Rashyd, Zaaboul. (2021). *IPCC Sixth Assessment Report Working Group I Chapter 12: Climate change information for regional impact and for risk assessment*.
- Razzak, Weshah A. (2022). "The Econometrics of Global Warming," *Journal of Economics and Econometrics*, vol. 65(2), pages 13-47.
- Resources for the Future (RFF) (2025). Global Energy Outlook online reference tool <https://www.rff.org/publications/data-tools/global-energy-outlook/> accessed April 18, 2025.
- Ring, M.J., D. Lindner, E.F. Cross and M. E. Schlesinger (2012) Causes of the Global Warming Observed since the 19th Century. *Atmospheric and Climate Sciences*, 2, 401-415. https://file.scirp.org/pdf/ACS20120400002_59142760.pdf
- Ritchie, Hannah Pablo Rosado, and Max Roser (2024) - "CO₂ emissions by fuel" Published online in 2020 at OurWorldinData.org, updated 2024. Retrieved from: 'https://ourworldindata.org/emissions-by-fuel' [Online Resource]
- Roe GH, Baker MB (2007) Why is climate sensitivity so unpredictable? *Science* 318:629–632
- Rutgers University Snow Lab (undated) <http://climate.rutgers.edu/snowcover/index.php>
- Scaffeta, N (2023) CMIP6 GCM ensemble members versus global surface temperatures. *Climate Dynamics* 60, 3091–3120 (2023). <https://doi.org/10.1007/s00382-022-06493-w>
- Schelling, Thomas C (1992) Some economics of global warming. *The American Economic Review*, 82 (1):1–14.
- Schwartz, Stephen E., Robert J. Charlson and Henning Rodhe (2007) Quantifying climate change — too rosy a picture? *Nature Reports-Climate Change* Vol 2 pp. 23-24.
- Seager, R., Cane, M., Henderson, N., Lee, D. E., Abernathey, R., and Zhang, H. (2019): Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases, *Nat. Clim. Change*, 9, 517-522, <https://doi.org/10.1038/s41558-019-0505-x>, 2019
- Sen Gupta, Alexander & Jourdain, Nicolas & Brown, Jaclyn & Monselesan, Didier. (2013). Climate drift in the CMIP5 models. *Journal of Climate*. 26. 8597-8615. 10.1175/JCLI-D-12-00521.1.
- Shaviv, Nir J., Henrik Svensmark and Jan Veizer (2023) *Annals of the New York Academy of Sciences* 1519:7—19. <https://nyaspubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1111/nyas.14920>
- Sherwood, S. C., and Forest, C. E.: (2024) Opinion: Can uncertainty in climate sensitivity be narrowed further?, *Atmospheric Chemistry and Physics*, 24, 2679-2686, <https://doi.org/10.5194/acp-24-2679-2024>.
- Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., Hegerl, G., Klein, S. A., Marvel, K. D., Rohling, E. J., Watanabe, M., Andrews, T., Braconnot, P., Bretherton, C. S., Foster, G. L., Hausfather, Z., Heydt, A. S., Knutti, R., Mauritsen, T., Norris, J. R., Proistosescu, C., Rugenstein, M., Schmidt, G. A., Tokarska, K. B., and Zelinka, M. D. (2020) An Assessment of Earth's Climate

- Sensitivity Using Multiple Lines of Evidence, *Review of Geophysics*, 58, <https://doi.org/10.1029/2019RG000678>.
- Simpson, I et al. (2024) Observed humidity trends in dry regions contradict climate models. *Proceedings of the National Academy of Sciences* 2024 Vol. 121 No. 1 e2302480120 <https://www.pnas.org/doi/10.1073/pnas.2302480120>
- Skeie, R.B., T. Berntsen, M. Aldrin, M. Holden, and G. Myhre. A lower and more constrained estimate of climate sensitivity using updated observations and detailed radiative forcing time series (2014) *Earth System Dynamics* 5, 139–175, 2014 doi:10.5194/esd-5-139-2014. <https://search.proquest.com/openview/05f113e95581027c9a9f0f0a2a1551ac/>
- Spencer, Roy (2024) Global Warming: Observations vs. Climate Models. Heritage Foundation January 2024 <https://www.heritage.org/environment/report/global-warming-observations-vs-climate-models>
- Spencer, Roy W. and John R. Christy (2024) Effective climate sensitivity distributions from a 1D model of global ocean and land temperature trends, 1970–2021 *Theoretical and Applied Climatology* 155 pp. 299–308. <https://link.springer.com/article/10.1007/s00704-023-04634-7>
- Stansfield et al. (2020) “Changes in Precipitation From North Atlantic Tropical Cyclones Under RCP Scenarios in the Variable-Resolution Community Atmosphere Model” *Geophys. Res. Letters* <https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2019GL086930>
- Stern, D and R. Kaufmann (2000) “Detecting a global warming signal in hemispheric temperature series: A structural time series analysis.” *Climatic Change* 47:411–438.
- Storm, S (2017) “How the Invisible Hand is Supposed to Adjust the Natural Thermostat: A Guide for the Perplexed.” *Science and Engineering Ethics* vol 23: 1307—1331.
- Taylor, Charles and Wolfram Schlenker (2023) Environmental drivers of agricultural productivity growth: CO2 fertilization of US field crops. National Bureau of Economic Research Working paper 29320, <http://www.nber.org/paper/w29320>
- Tol, Richard (2002) “Estimates of the Damage Costs of Climate Change” *Environmental and Resource Economics* 21:47—73
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, “Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review”, EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf
- Vogelsang, T and N. Nawaz (2016) “Estimation and Inference of Linear Trend Slope Ratios With an Application to Global Temperature Data.” *Journal of Time Series Analysis* doi.org/10.1111/jtsa.12209 <https://onlinelibrary.wiley.com/doi/abs/10.1111/jtsa.12209>
- Wehner, M.F., J.R. Arnold, T. Knutson, K.E. Kunkel, and A.N. LeGrande, 2017: Droughts, floods, and wildfires. In: *Climate Science Special Report: Fourth National Climate Assessment*, Volume I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 231–256 doi: 10.7930/J0CJ8BNN.
- Wigley, T.M.L. (1998). “The Kyoto Protocol: CO2, CH4 and climate implications.” *Geophysical Research Letters* 25(13), 2285–2288
- Yang, Yimin, Fei Jia, and Haoran Li. Estimation of panel data models with mixed sampling frequencies (2023). *Oxford Bulletin of Economics and Statistics*, 85(3):514–544.
- Zhao, Xiaobing, Mason Gerety, and Nicolai V. Kuminoff (2018) Revisiting the temperature-economic growth relationship using global subnational data. *Journal of environmental management*, 223:537–544, 2018.



An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America

CONFIDENTIAL DRAFT FOR DISCUSSION PURPOSES

Climate Analysis Group
United States Department of Energy
May 28, 2025

CONFIDENTIAL DRAFT FOR DISCUSSION PURPOSES

An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America

Report to US Energy Secretary Christopher Wright
May 28, 2025

Climate Analysis Group:

John Christy, Ph.D.
Judith Curry, Ph.D.
Steven Koonin, Ph.D.
Ross McKittrick, Ph.D.
Roy Spencer, Ph.D.

Copyright © 2025 United States

Suggested citation:

Climate Analysis Group (2025) An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America. Washington DC: Department of Energy, May 24 2025.

Table of Contents

SECRETARY’S PREFACE	IV
INTRODUCTION: OVERVIEW AND PURPOSE OF THIS DOCUMENT.....	V
PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE CLIMATE	1
1 CHAPTER TITLE	2
1.1 SUBHEADING	2
1.1.1 Further subheading	2
PART II: CLIMATE RESPONSE TO CO ₂ EMISSIONS	3
2 CHAPTER TITLE	4
2.1 SUBHEADING	4
2.1.1 Further subheading	4
PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY	5
3 CHAPTER TITLE	6
3.1 SUBHEADING	6
3.1.1 Further subheading	6
ABOUT THE AUTHORS.....	7

SECRETARY'S PREFACE

Text

INTRODUCTION: OVERVIEW AND PURPOSE OF THIS DOCUMENT

Text.

PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE CLIMATE

1 CHAPTER TITLE

1.1 Subheading

Text of section.

1.1.1 Further subheading

Text of section.

PART II: CLIMATE RESPONSE TO CO₂ EMISSIONS

2 CHAPTER TITLE

2.1 Subheading

Text of section.

2.1.1 Further subheading

Text of section.

PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

3 CHAPTER TITLE

3.1 Subheading

Text of section.

3.1.1 Further subheading

Text of section.

ABOUT THE AUTHORS

Executive Summary

1. Carbon dioxide as a pollutant

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Contaminants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

2 Direct Impacts of CO₂ on the environment

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water reduces the alkalinity of the oceans. The recent decline in alkalinity is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Declining alkalinity might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

3 Human influences on the climate

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. Models disagree over the rate of land and ocean CO₂ uptake but all agree that it has been increasing since 1959.

4 Climate Sensitivity to CO₂ Forcing

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

5 Models versus Observations in the Recent Past

Climate models show warming biases in many aspects of their reproduction of the past few decades. In response to observed changes in forcing inputs they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The IPCC has acknowledged some of these issues but not all.

6 Extreme weather

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfires are not more common in the US than they were in the 1980s. Burned area increased from the 1960s to the early 2000's however it is low compared to the estimated natural baseline level. US wildfire activity is strongly affected by forest management practices.

7 Changes in Sea level

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. US tide gauge measurements shown herein reveal no obvious acceleration beyond the historical average rate of sea level rise.

8 Uncertainties in Climate Change Attribution

"Attribution" refers to determining cause regarding some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not in general make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (e.g. event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

9. Climate change and US agriculture

There is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behavior by farmers, has been beneficial for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

10. Managing Risks of Extreme Weather

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase as long as people are able to undertake adaptive responses.

11 Climate change, the economy and the Social Cost of Carbon

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the AR5. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points at present does not justify major revisions to SCC estimates.

12 Global climate impacts of U.S. emissions policies

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

Ad Hoc Climate Science Research Team

An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States

Report to the Secretary, US Department of Energy

May 30, 2025

John Christy, Ph.D.
Judith Curry, Ph.D.
Steven Koonin, Ph.D.
Ross McKittrick, Ph.D.
Roy Spencer, Ph.D.

Table of Contents

Secretary's Preface

Introduction: Overview and purpose of document

Part I: Direct human influence on ecosystems and the climate

- 1 Carbon dioxide and air pollution
- 2 Direct impacts of CO₂ on the environment
 - 2.1 Land- Global Greening
 - 2.2 Ocean - alkalinity
- 3 Anthropogenic Radiative forcing
 - 3.1 Components of anthropogenic radiative forcing and their history to date
 - 3.2 The carbon cycle and future emission scenarios
 - 3.3 Aerosols and the uncertainties associated with them

Part II: Climate response to CO₂ emissions

- 4 Measuring climate sensitivity to CO₂ doubling
- 5 Models versus observations in recent past
- 6 Evidence on trends and attributable changes in extreme weather
- 7 Sea level rise
- 8 Uncertainties in analysis of attribution

Part III: Impacts on ecosystems and society

- 9 Climate change and US agriculture
- 10 Managing risks of extreme weather
- 11 Mortality risk from extreme heat and cold
- 12 Climate change and the Economy
 - 12.1 Climate change and economic growth
 - 12.2 The Social Cost of Carbon
- 13 US vehicle-based CO₂ emissions and the global climate

References

9 Uncertainties in Climate Change Attribution

9.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause.¹ As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement:

¹ Note that the IPCC definition of “climate change” allows for both natural and human causes. This differs from the UNFCCC definition (and common usage), where the term is limited to human causes.

(Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

9.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

9.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

9.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. This minimal contribution of natural variability has been disputed by a number of publications that question the magnitudes of solar variability and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is

higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large

relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the

timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

9.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999)

methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

9.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called

vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

9.4 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest when assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

Table 12.12 in Ranasinghe et al. (2021, p. 1856) summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across 33 CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to understate the importance of natural variability and overstate the anthropogenic influence. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability. The reported findings are summarized in Table 9.1.

CID Type	Number of CIDs	Anthropogenic signal detected	Anthropogenic signal not detected
Heat and Cold	4	3 (mean temperature, extreme heat, cold spells)	1 (frost)
Wet and Dry	8	0	8 (mean precipitation, flooding, landslide, dryness and drought, fire weather)

Wind	4	0	4 (mean wind speed, severe storms, tropical cyclones, sand and dust storms)
Snow and Ice	6	2 (permafrost, ice cover)	4 (snow, glacier and ice sheet, heavy snowfall and ice storm events, hail, avalanche)
Coastal	3	0	3 (relative sea level, coastal flooding, coastal erosion)
Open Ocean	5	3 (mean temperature, salinity, dissolved oxygen)	2 (marine heatwaves, ocean acidity)
Other	3	1 (surface CO ₂ level)	2 (air pollution weather, radiation at surface)
TOTAL	33	9	24

Table 9.1: Emergence of anthropogenic signals in Climate Impact Drivers. Adapted from IPCC AR6 WGI Table 12.12.

The CID types that attract the most public concern are those related to temperature (Heat and Cold), precipitation (Wet and Dry), Wind and Coastal changes. Of the 19 CIDs identified under those headings the IPCC reports an attributable anthropogenic signal in only 3, one of which (a decline in cold spells) is a beneficial change. No attributable change is reported in any category of precipitation, wind or coastal change events. Of the 9 CIDs where an attributable anthropogenic change is detected, 3 relate to changes in chemistry (surface CO₂ levels, ocean salinity and dissolved oxygen) rather than weather.

Table 12.12 in Ranasinghe et al. (2021) contains columns indicating whether a signal of attributable anthropogenic influence is expected to emerge by, respectively, 2050 or 2100. Unfortunately they rely on the RCP8.5 scenario which as we discussed in Chapter is biased upwards. Even still they expect the emergence of relatively few anthropogenic signals in CIDs.

We discussed data on extreme weather in Chapter 7. A point we emphasized therein was that, despite commonly-heard claims that all types of extreme weather are getting worse due to human activity, few significant trends in most weather types can be detected due to high levels of natural variability over long time scales. Table 9.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible.

9.5 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened

since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today’s climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA’s tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA’s work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an

outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an “ordinary” weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second “heatwave” regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case study from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

9.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.

- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

9.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

1. Intergovernmental Panel on Climate Change. *IPCC Glossary*. Accessed May 2, 2025. <https://apps.ipcc.ch/glossary/>.
2. G. C. Hegerl et al., “Understanding and Attributing Climate Change,” in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 663–745.
3. J. T. Houghton et al., eds., *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press, 2001), 1–881.
4. W. Cramer et al., “Detection and Attribution of Observed Impacts,” in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. C. B. Field et al. (Cambridge: Cambridge University Press, 2014), 979–1037.
5. Intergovernmental Panel on Climate Change, *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 10.

6. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker et al. (Cambridge: Cambridge University Press, 2013), 17.
7. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2021), 10.
8. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate,” *Research in Astronomy and Astrophysics* 21, no. 6 (2021): 131, <https://doi.org/10.1088/1674-4527/21/6/131>.
9. Willie Soon et al., “The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data,” *Climate* 11, no. 9 (2023): 179, <https://doi.org/10.3390/cli11090179>.
10. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records,” *Geoscience Frontiers* 14, no. 6 (November 2023): 101650, <https://doi.org/10.1016/j.gsf.2023.101650>.
11. Gunnar Myhre et al., “Anthropogenic and Natural Radiative Forcing,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge: Cambridge University Press, 2014), 659–740, <https://doi.org/10.1017/CBO9781107415324.018>.
12. Sergey K. Gulev et al., “Changing State of the Climate System,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Geneva: Intergovernmental Panel on Climate Change, 2021), 287–422.
11. Katja Matthes et al., “Solar Forcing for CMIP6 (v3.2),” *Geoscientific Model Development* 10, no. 6 (June 22, 2017): 2247–2302, <https://doi.org/10.5194/gmd-10-2247-2017>.
12. Mike Lockwood, “Solar Influence on Global and Regional Climates,” *Surveys in Geophysics* 33, no. 3–4 (May 16, 2012): 503–534, <https://doi.org/10.1007/s10712-012-9181-3>.
13. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate.”
14. Nicola Scafetta et al., “Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018,” *Remote Sensing* 11, no. 21 (November 1, 2019): 2569, <https://doi.org/10.3390/rs11212569>.
14. V. M. Velasco Herrera, B. Mendoza, and G. Velasco Herrera, “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
15. Theodosios Chatzistergos, Natalie A. Krivova, and Kok Leng Yeo, “Long-Term Changes in Solar Activity and Irradiance,” *Journal of Atmospheric and Solar-Terrestrial Physics* 252 (November 2023): 106150, <https://doi.org/10.1016/j.jastp.2023.106150>.
16. S. K. Solanki et al., “Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years,” *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, <https://doi.org/10.1038/nature02995>.
17. I. G. Usoskin, S. K. Solanki, and G. A. Kovaltsov, “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, <https://doi.org/10.1051/0004-6361:20077704>.

18. Werner K. Schmutz, “Changes in the Total Solar Irradiance and Climatic Effects,” *Journal of Space Weather and Space Climate* 11 (2021): 40, <https://doi.org/10.1051/swsc/2021016>.
19. Nicola Scafetta, “Discussion on Climate Oscillations: CMIP5 General Circulation Models versus a Semi-Empirical Harmonic Model Based on Astronomical Cycles,” *Earth-Science Reviews* 126 (November 2013): 321–357, <https://doi.org/10.1016/j.earscirev.2013.08.008>.
20. Frank Stefani, “Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions,” *Climate* 9, no. 11 (November 3, 2021): 163, <https://doi.org/10.3390/cli9110163>.
21. Ronan Connolly et al., “Challenges in the Detection and Attribution of Northern Hemisphere Surface Temperature Trends Since 1850,” *Research in Astronomy and Astrophysics* 23, no. 10 (2023): 105015, <https://doi.org/10.1088/1674-4527/acf18e>.
22. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records.”
24. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis*.
25. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis*.
26. Ibid.
27. J. D. McLean, C. R. de Freitas, and R. M. Carter, “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
28. Ka-Kit Tung and Jiansong Zhou, “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
29. Petr Chylek et al., “The Role of Atlantic Multi-Decadal Oscillation in the Global Mean Temperature Variability,” *Climate Dynamics* 47, no. 9–10 (February 20, 2016): 3271–3279, <https://doi.org/10.1007/s00382-016-3025-7>.
30. Nicola Scafetta, “Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature,” *Atmosphere* 12, no. 2 (2021): 147, <https://doi.org/10.3390/atmos12020147>.
31. Ross McKittrick, “Checking for Model Consistency in Optimal Fingerprinting: A Comment,” *Climate Dynamics* 58, no. 1–2 (2022): 405–411, <https://doi.org/10.1007/s00382-021-05913-7>.
32. M. R. Allen and S. F. B. Tett, “Checking for Model Consistency in Optimal Fingerprinting,” *Climate Dynamics* 15, no. 6 (1999): 419–434, <https://doi.org/10.1007/s003820050291>.
33. Ross McKittrick, Timothy Vogelsang, and John Christy, “Temperature Trends, Climate Attribution and the Nonstationarity Question,” *Earth System Dynamics Discussions* (2023): <https://doi.org/10.5194/esd-2023-11>.
34. Ross McKittrick, “Total Least Squares Bias in Climate Fingerprinting Regressions with Heterogeneous Noise Variances and Correlated Explanatory Variables,” *Environmetrics* 35, no. 2 (March 2024): e2835, <https://doi.org/10.1002/env.2835>.
35. S. Seneviratne et al., “Chapter 11: Weather and Climate Extreme Events in a Changing Climate.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
36. R. Ranasinghe et al., “Chapter 12: Climate Change Information for Regional Impact and for Risk Assessment.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I*

- to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1767–1926. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.014>.
37. National Academies of Sciences, Engineering, and Medicine. *Attribution of Extreme Weather and Climate Events and Their Impacts*. Washington, DC: The National Academies Press, forthcoming. <https://www.nationalacademies.org/our-work/attribution-of-extreme-weather-and-climate-events-and-their-impacts>.
 38. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021: Synoptic/Mesoscale Conditions and Climate Perspective,” *Weather and Forecasting* 39, no. 2 (February 2024): 275–291, <https://doi.org/10.1175/WAF-D-23-0154.1>.
 39. World Weather Attribution. “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
 40. S.Y. Philip et al., “Rapid Attribution Analysis of the Extraordinary Heatwave on the Pacific Coast of the US and Canada June 2021,” *Earth System Dynamics* 13, no. 4 (December 8, 2022): 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>.
 41. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021.”
 42. Emily Bercos-Hickey et al., “Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave,” *Geophysical Research Letters* 49, no. 23 (December 2022): e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
 43. Judea Pearl, *Causality* (Cambridge: Cambridge University Press, 2009).
 44. Geert Jan van Oldenborgh et al., “Attributing and Projecting Heatwaves Is Hard: We Can Do Better,” *Earth’s Future* 10, no. 6 (June 2022): e2021EF002271, <https://doi.org/10.1029/2021EF002271>.
 45. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming,” NOAA Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division, 2017, <https://www.aoml.noaa.gov/hrd/Landsea/harvey-global-warming.pdf>.
 46. David M. Roth, “Tropical Cyclone Rainfall for the North Atlantic Basin,” Weather Prediction Center, National Oceanic and Atmospheric Administration, 2017, <https://www.wpc.ncep.noaa.gov/tropical/rain/tcmaxima.html>.
 47. Geert Jan van Oldenborgh et al., “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017,” *Environmental Research Letters* 12, no. 12 (December 2017): 124009, <https://doi.org/10.1088/1748-9326/aa9ef2>.
 48. Kerry Emanuel, “Assessing the Present and Future Probability of Hurricane Harvey’s Rainfall,” *Proceedings of the National Academy of Sciences* 114, no. 48 (November 28, 2017): 12681–12684, <https://doi.org/10.1073/pnas.1716222114>.
 49. Mark D. Risser and Michael F. Wehner, “Attributable Human-Induced Changes in the Likelihood and Magnitude of the Observed Extreme Precipitation During Hurricane Harvey,” *Geophysical Research Letters* 44, no. 24 (December 2017): 12,457–12,464, <https://doi.org/10.1002/2017GL075888>.
 50. Kevin E. Trenberth et al., “Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation,” *Earth’s Future* 6, no. 5 (May 2018): 730–744, <https://doi.org/10.1029/2018EF000825>.
 51. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming.”
 52. Yog Aryal et al., “Long Term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño–Southern

Oscillation,” *Journal of Hydrology* 559 (2018): 698–710,
<https://doi.org/10.1016/j.jhydrol.2018.02.072>.

Ranasinghe, R., A.C. Ruane, R. Vautard, N. Arnell, E. Coppola, F.A. Cruz, S. Dessai, A.S. Islam, M. Rahimi, D. Ruiz Carrascal, J. Sillmann, M.B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul, (2021): Climate Change Information for Regional Impact and for Risk Assessment. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1767–1926, doi:[10.1017/9781009157896.014](https://doi.org/10.1017/9781009157896.014).

Jones, Gareth, Peter A. Stott and John F.B. Mitchell (2016) Uncertainties in the Attribution of Greenhouse Gas Warming and Implications for Climate Prediction. *Journal of Geophysical Research-Atmospheres* 121(12) 6969—6992 <https://doi.org/10.1002/2015JD024337>.

Kravtsov, S., A. Westgate and A. Gavrilov (2024) Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics* Volume 62, pages 10281–10306 <https://link.springer.com/article/10.1007/s00382-024-07451-4>

Weinkle, Jessica (2025) Carnival mirrors: How concentrated is the event attribution literature? Substack essay <https://jessicaweinkle.substack.com/p/how-big-is-the-event-attribution>

Chen, Chung and Lon-Mu Liu (1993) Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association* Vol. 88, No. 421 (Mar., 1993), pp 284—297. <http://www.jstor.org/stable/2290724>

Sardeshmukh, Prashant D., Gilbert P. Compo and Cécile Penland (2015) Need for Caution in Interpreting Extreme Weather Statistics *Journal of Climate* 28(23) 9166–9187 <https://journals.ametsoc.org/view/journals/clim/28/23/jcli-d-15-0020.1.xml>

Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 <https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>

Miralles, Ophélie and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 <https://doi.org/10.1016/j.wace.2023.100584>

Barlow, Anna Maria, Chris Sherlock and Jonathan Tawn (2020) Inference for Extreme Values Under Threshold-Based Stopping Rules. *Journal of the Royal Statistical Society Series C* August 2020, Pages 765–789, <https://doi.org/10.1111/rssc.12420>

Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. <https://doi.org/10.1029/2023GL104090>

Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. <https://blogs.oregonstate.edu/occri/oregon-climate-assessments> .

McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? Geophysical Research Letters, 49, e2022GL100380. <https://doi.org/10.1029/2022GL100380>

Bercos-Hickey et al. (2022) Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave. Geophysical Research Letters 49 <https://doi.org/10.1029/2022GL099396>

Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay <https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>

9 Uncertainties in Climate Change Attribution

9.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause.¹ As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement:

¹ Note that the IPCC definition of “climate change” allows for both natural and human causes. This differs from the UNFCCC definition (and common usage), where the term is limited to human causes.

(Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

9.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

9.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

9.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. This minimal contribution of natural variability has been disputed by a number of publications that question the magnitudes of solar variability and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is

higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large

relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the

timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

9.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999)

methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

9.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called

vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

9.4 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest when assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

Table 12.12 in Ranasinghe et al. (2021, p. 1856) summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability. The reported findings are listed in Table 9.1 which adapts IPCC AR6 Table 12.12.²

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO

² We have separated polar sea ice into Arctic and Antarctic categories for clarity, and removed ground-level CO₂ as a CID since claiming anthropogenic signal due to CO₂ emissions is a tautology.

Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 9.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Several patterns stand out. First, out of the 34 weather impact categories an anthropogenic signal is asserted with *high confidence* in only four, and with *medium confidence* in a further four. For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the four *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Second, as shown in columns 2 and 3 the IPCC expects very few such signals to emerge this century even under the most extreme forcing scenario. As we discuss in Chapter 4 the RCP8.5 scenario is an implausible high-end storyline, it is not a “base case” or business-as-usual

projection. Yet even still most weather impacts are not expected to exhibit an anthropogenic signal this century. As we discussed in Chapter 7 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time.

A point we emphasized in Chapter 7 was that, despite commonly-heard claims that all types of extreme weather are getting worse due to human activity, few significant trends in most weather types can be detected due to high levels of natural variability over long time scales. Table 9.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

9.5 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA's tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case study from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

9.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today's climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of

global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

9.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no

evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

1. Intergovernmental Panel on Climate Change. *IPCC Glossary*. Accessed May 2, 2025. <https://apps.ipcc.ch/glossary/>.
2. G. C. Hegerl et al., “Understanding and Attributing Climate Change,” in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 663–745.
3. J. T. Houghton et al., eds., *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press, 2001), 1–881.
4. W. Cramer et al., “Detection and Attribution of Observed Impacts,” in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. C. B. Field et al. (Cambridge: Cambridge University Press, 2014), 979–1037.
5. Intergovernmental Panel on Climate Change, *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 10.
6. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker et al. (Cambridge: Cambridge University Press, 2013), 17.
7. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2021), 10.
8. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate,” *Research in Astronomy and Astrophysics* 21, no. 6 (2021): 131, <https://doi.org/10.1088/1674-4527/21/6/131>.
9. Willie Soon et al., “The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data,” *Climate* 11, no. 9 (2023): 179, <https://doi.org/10.3390/cli11090179>.
10. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records,” *Geoscience Frontiers* 14, no. 6 (November 2023): 101650, <https://doi.org/10.1016/j.gsf.2023.101650>.
11. Gunnar Myhre et al., “Anthropogenic and Natural Radiative Forcing,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge: Cambridge University Press, 2014), 659–740, <https://doi.org/10.1017/CBO9781107415324.018>.
12. Sergey K. Gulev et al., “Changing State of the Climate System,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Geneva: Intergovernmental Panel on Climate Change, 2021), 287–422.
11. Katja Matthes et al., “Solar Forcing for CMIP6 (v3.2),” *Geoscientific Model Development* 10, no. 6 (June 22, 2017): 2247–2302, <https://doi.org/10.5194/gmd-10-2247-2017>.

12. Mike Lockwood, “Solar Influence on Global and Regional Climates,” *Surveys in Geophysics* 33, no. 3–4 (May 16, 2012): 503–534, <https://doi.org/10.1007/s10712-012-9181-3>.
13. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate.”
14. Nicola Scafetta et al., “Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018,” *Remote Sensing* 11, no. 21 (November 1, 2019): 2569, <https://doi.org/10.3390/rs11212569>.
14. V. M. Velasco Herrera, B. Mendoza, and G. Velasco Herrera, “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
15. Theodosios Chatzistergos, Natalie A. Krivova, and Kok Leng Yeo, “Long-Term Changes in Solar Activity and Irradiance,” *Journal of Atmospheric and Solar-Terrestrial Physics* 252 (November 2023): 106150, <https://doi.org/10.1016/j.jastp.2023.106150>.
16. S. K. Solanki et al., “Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years,” *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, <https://doi.org/10.1038/nature02995>.
17. I. G. Usoskin, S. K. Solanki, and G. A. Kovaltsov, “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, <https://doi.org/10.1051/0004-6361:20077704>.
18. Werner K. Schmutz, “Changes in the Total Solar Irradiance and Climatic Effects,” *Journal of Space Weather and Space Climate* 11 (2021): 40, <https://doi.org/10.1051/swsc/2021016>.
19. Nicola Scafetta, “Discussion on Climate Oscillations: CMIP5 General Circulation Models versus a Semi-Empirical Harmonic Model Based on Astronomical Cycles,” *Earth-Science Reviews* 126 (November 2013): 321–357, <https://doi.org/10.1016/j.earscirev.2013.08.008>.
20. Frank Stefani, “Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions,” *Climate* 9, no. 11 (November 3, 2021): 163, <https://doi.org/10.3390/cli9110163>.
21. Ronan Connolly et al., “Challenges in the Detection and Attribution of Northern Hemisphere Surface Temperature Trends Since 1850,” *Research in Astronomy and Astrophysics* 23, no. 10 (2023): 105015, <https://doi.org/10.1088/1674-4527/acf18e>.
22. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records.”
24. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis*.
25. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis*.
26. Ibid.
27. J. D. McLean, C. R. de Freitas, and R. M. Carter, “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
28. Ka-Kit Tung and Jiansong Zhou, “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
29. Petr Chylek et al., “The Role of Atlantic Multi-Decadal Oscillation in the Global Mean Temperature Variability,” *Climate Dynamics* 47, no. 9–10 (February 20, 2016): 3271–3279, <https://doi.org/10.1007/s00382-016-3025-7>.

30. Nicola Scafetta, “Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature,” *Atmosphere* 12, no. 2 (2021): 147, <https://doi.org/10.3390/atmos12020147>.
31. Ross McKittrick, “Checking for Model Consistency in Optimal Fingerprinting: A Comment,” *Climate Dynamics* 58, no. 1–2 (2022): 405–411, <https://doi.org/10.1007/s00382-021-05913-7>.
32. M. R. Allen and S. F. B. Tett, “Checking for Model Consistency in Optimal Fingerprinting,” *Climate Dynamics* 15, no. 6 (1999): 419–434, <https://doi.org/10.1007/s003820050291>.
33. Ross McKittrick, Timothy Vogelsang, and John Christy, “Temperature Trends, Climate Attribution and the Nonstationarity Question,” *Earth System Dynamics Discussions* (2023): <https://doi.org/10.5194/esd-2023-11>.
34. Ross McKittrick, “Total Least Squares Bias in Climate Fingerprinting Regressions with Heterogeneous Noise Variances and Correlated Explanatory Variables,” *Environmetrics* 35, no. 2 (March 2024): e2835, <https://doi.org/10.1002/env.2835>.
35. S. Seneviratne et al., “Chapter 11: Weather and Climate Extreme Events in a Changing Climate.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
36. R. Ranasinghe et al., “Chapter 12: Climate Change Information for Regional Impact and for Risk Assessment.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1767–1926. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.014>.
37. National Academies of Sciences, Engineering, and Medicine. *Attribution of Extreme Weather and Climate Events and Their Impacts*. Washington, DC: The National Academies Press, forthcoming. <https://www.nationalacademies.org/our-work/attribution-of-extreme-weather-and-climate-events-and-their-impacts>.
38. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021: Synoptic/Mesoscale Conditions and Climate Perspective,” *Weather and Forecasting* 39, no. 2 (February 2024): 275–291, <https://doi.org/10.1175/WAF-D-23-0154.1>.
39. World Weather Attribution. “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
40. S.Y. Philip et al., “Rapid Attribution Analysis of the Extraordinary Heatwave on the Pacific Coast of the US and Canada June 2021,” *Earth System Dynamics* 13, no. 4 (December 8, 2022): 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>.
41. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021.”
42. Emily Bercos-Hickey et al., “Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave,” *Geophysical Research Letters* 49, no. 23 (December 2022): e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
43. Judea Pearl, *Causality* (Cambridge: Cambridge University Press, 2009).
44. Geert Jan van Oldenborgh et al., “Attributing and Projecting Heatwaves Is Hard: We Can Do Better,” *Earth’s Future* 10, no. 6 (June 2022): e2021EF002271, <https://doi.org/10.1029/2021EF002271>.

45. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming,” NOAA Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division, 2017, <https://www.aoml.noaa.gov/hrd/Landsea/harvey-global-warming.pdf>.
46. David M. Roth, “Tropical Cyclone Rainfall for the North Atlantic Basin,” Weather Prediction Center, National Oceanic and Atmospheric Administration, 2017, <https://www.wpc.ncep.noaa.gov/tropical/rain/tcmaxima.html>.
47. Geert Jan van Oldenborgh et al., “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017,” *Environmental Research Letters* 12, no. 12 (December 2017): 124009, <https://doi.org/10.1088/1748-9326/aa9ef2>.
48. Kerry Emanuel, “Assessing the Present and Future Probability of Hurricane Harvey’s Rainfall,” *Proceedings of the National Academy of Sciences* 114, no. 48 (November 28, 2017): 12681–12684, <https://doi.org/10.1073/pnas.1716222114>.
49. Mark D. Risser and Michael F. Wehner, “Attributable Human-Induced Changes in the Likelihood and Magnitude of the Observed Extreme Precipitation During Hurricane Harvey,” *Geophysical Research Letters* 44, no. 24 (December 2017): 12,457–12,464, <https://doi.org/10.1002/2017GL075888>.
50. Kevin E. Trenberth et al., “Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation,” *Earth’s Future* 6, no. 5 (May 2018): 730–744, <https://doi.org/10.1029/2018EF000825>.
51. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming.”
52. Yog Aryal et al., “Long Term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño–Southern Oscillation,” *Journal of Hydrology* 559 (2018): 698–710, <https://doi.org/10.1016/j.jhydrol.2018.02.072>.

Ranasinghe, R., A.C. Ruane, R. Vautard, N. Arnell, E. Coppola, F.A. Cruz, S. Dessai, A.S. Islam, M. Rahimi, D. Ruiz Carrascal, J. Sillmann, M.B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul, (2021): Climate Change Information for Regional Impact and for Risk Assessment. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1767–1926, doi:[10.1017/9781009157896.014](https://doi.org/10.1017/9781009157896.014).

Jones, Gareth, Peter A. Stott and John F.B. Mitchell (2016) Uncertainties in the Attribution of Greenhouse Gas Warming and Implications for Climate Prediction. *Journal of Geophysical Research-Atmospheres* 121(12) 6969—6992 <https://doi.org/10.1002/2015JD024337>.

Kravtsov, S., A. Westgate and A. Gavrilov (2024) Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics* Volume 62, pages 10281–10306 <https://link.springer.com/article/10.1007/s00382-024-07451-4>

Weinkle, Jessica (2025) Carnival mirrors: How concentrated is the event attribution literature? Substack essay <https://jessicaweinkle.substack.com/p/how-big-is-the-event-attribution>

- Chen, Chung and Lon-Mu Liu (1993) Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association* Vol. 88, No. 421 (Mar., 1993), pp 284—297. <http://www.jstor.org/stable/2290724>
- Sardeshmukh, Prashant D., Gilbert P. Compo and Cécile Penland (2015) Need for Caution in Interpreting Extreme Weather Statistics *Journal of Climate* 28(23) 9166–9187 <https://journals.ametsoc.org/view/journals/clim/28/23/jcli-d-15-0020.1.xml>
- Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 <https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>
- Miralles, Ophélie and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 <https://doi.org/10.1016/j.wace.2023.100584>
- Barlow, Anna Maria, Chris Sherlock and Jonathan Tawn (2020) Inference for Extreme Values Under Threshold-Based Stopping Rules. *Journal of the Royal Statistical Society Series C* August 2020, Pages 765–789, <https://doi.org/10.1111/rssc.12420>
- Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. <https://doi.org/10.1029/2023GL104090>
- Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. <https://blogs.oregonstate.edu/occri/oregon-climate-assessments> .
- McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophysical Research Letters*, 49, e2022GL100380. <https://doi.org/10.1029/2022GL100380>
- Bercos-Hickey et al. (2022) Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave. *Geophysical Research Letters* 49 <https://doi.org/10.1029/2022GL099396>
- Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay <https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>

9 Uncertainties in Climate Change Attribution

9.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause.¹ As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement:

¹ Note that the IPCC definition of “climate change” allows for both natural and human causes. This differs from the UNFCCC definition (and common usage), where the term is limited to human causes.

(Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

9.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

9.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

9.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. This minimal contribution of natural variability has been disputed by a number of publications that question the magnitudes of solar variability and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is

higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large

relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Nino-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the

timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

9.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999)

methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

9.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called

vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

9.4 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” For instance under the heading “Heat and Cold” the CIDs are mean air temperature, extreme heat, cold spells and frost. They also point out that depending on the system in question, CIDs can be detrimental, neutral, beneficial or a mixture of each. Table 12.12 in Ranasinghe et al. (2021, p. 1856) summarizes the AR6 assessment of whether a signal of anthropogenic influence has emerged across 33 CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to understate the importance of natural variability and overstate the anthropogenic influence. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability. The reported findings are shown in Table 9.1.

CID Type	Number of CIDs	Anthropogenic signal detected	Anthropogenic signal not detected
Heat and Cold	4	3 (mean temperature, extreme heat, cold spells)	1 (frost)
Wet and Dry	8	0	8 (mean precipitation, flooding, landslide, dryness and drought, fire weather)
Wind	4	0	4 (mean wind speed, severe storms, tropical cyclones, sand and dust storms)
Snow and Ice	6	2 (permafrost, ice cover)	4 (snow, glacier and ice sheet, heavy snowfall and

			ice storm events, hail, avalanche)
Coastal	3	0	3 (relative sea level, coastal flooding, coastal erosion)
Open Ocean	5	3 (mean temperature, salinity, dissolved oxygen)	2 (marine heatwaves, ocean acidity)
Other	3	1 (surface CO ₂ level)	2 (air pollution weather, radiation at surface)
TOTAL	33	9	24

Table 9.1: Emergence of anthropogenic signals in Climate Impact Drivers. Adapted from IPCC AR6 WGI Table 12.12.

The CID types that attract the most public concern are those related to temperature (Heat and Cold), precipitation (Wet and Dry), wind and coastal changes. Of the 19 CIDs listed under those headings the IPCC reports an attributable anthropogenic signal in only 3, one of which (a decline in cold spells) is a beneficial change. No attributable change is reported in any category of precipitation, wind or coastal change events. Of the 9 CIDs where an attributable anthropogenic change is detected

9.4 Extreme event attribution (EEA)

The IPCC AR6 provides an ambiguous assessment of the role of global warming in the historical record of extreme weather and climate events. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, Chapter 12 of WG1 (Table12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA;

worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA's tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the

problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case study from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

9.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today's climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by

a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

9.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

1. Intergovernmental Panel on Climate Change. *IPCC Glossary*. Accessed May 2, 2025. <https://apps.ipcc.ch/glossary/>.
2. G. C. Hegerl et al., “Understanding and Attributing Climate Change,” in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 663–745.
3. J. T. Houghton et al., eds., *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press, 2001), 1–881.
4. W. Cramer et al., “Detection and Attribution of Observed Impacts,” in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. C. B. Field et al. (Cambridge: Cambridge University Press, 2014), 979–1037.
5. Intergovernmental Panel on Climate Change, *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 10.
6. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker et al. (Cambridge: Cambridge University Press, 2013), 17.
7. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2021), 10.
8. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate,” *Research in Astronomy and Astrophysics* 21, no. 6 (2021): 131, <https://doi.org/10.1088/1674-4527/21/6/131>.
9. Willie Soon et al., “The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data,” *Climate* 11, no. 9 (2023): 179, <https://doi.org/10.3390/cli11090179>.
10. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records,” *Geoscience Frontiers* 14, no. 6 (November 2023): 101650, <https://doi.org/10.1016/j.gsf.2023.101650>.
11. Gunnar Myhre et al., “Anthropogenic and Natural Radiative Forcing,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the*

- Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge: Cambridge University Press, 2014), 659–740, <https://doi.org/10.1017/CBO9781107415324.018>.
12. Sergey K. Gulev et al., “Changing State of the Climate System,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Geneva: Intergovernmental Panel on Climate Change, 2021), 287–422.
 11. Katja Matthes et al., “Solar Forcing for CMIP6 (v3.2),” *Geoscientific Model Development* 10, no. 6 (June 22, 2017): 2247–2302, <https://doi.org/10.5194/gmd-10-2247-2017>.
 12. Mike Lockwood, “Solar Influence on Global and Regional Climates,” *Surveys in Geophysics* 33, no. 3–4 (May 16, 2012): 503–534, <https://doi.org/10.1007/s10712-012-9181-3>.
 13. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate.”
 14. Nicola Scafetta et al., “Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018,” *Remote Sensing* 11, no. 21 (November 1, 2019): 2569, <https://doi.org/10.3390/rs11212569>.
 14. V. M. Velasco Herrera, B. Mendoza, and G. Velasco Herrera, “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
 15. Theodosios Chatzistergos, Natalie A. Krivova, and Kok Leng Yeo, “Long-Term Changes in Solar Activity and Irradiance,” *Journal of Atmospheric and Solar-Terrestrial Physics* 252 (November 2023): 106150, <https://doi.org/10.1016/j.jastp.2023.106150>.
 16. S. K. Solanki et al., “Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years,” *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, <https://doi.org/10.1038/nature02995>.
 17. I. G. Usoskin, S. K. Solanki, and G. A. Kovaltsov, “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, <https://doi.org/10.1051/0004-6361:20077704>.
 18. Werner K. Schmutz, “Changes in the Total Solar Irradiance and Climatic Effects,” *Journal of Space Weather and Space Climate* 11 (2021): 40, <https://doi.org/10.1051/swsc/2021016>.
 19. Nicola Scafetta, “Discussion on Climate Oscillations: CMIP5 General Circulation Models versus a Semi-Empirical Harmonic Model Based on Astronomical Cycles,” *Earth-Science Reviews* 126 (November 2013): 321–357, <https://doi.org/10.1016/j.earscirev.2013.08.008>.
 20. Frank Stefani, “Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions,” *Climate* 9, no. 11 (November 3, 2021): 163, <https://doi.org/10.3390/cli9110163>.
 21. Ronan Connolly et al., “Challenges in the Detection and Attribution of Northern Hemisphere Surface Temperature Trends Since 1850,” *Research in Astronomy and Astrophysics* 23, no. 10 (2023): 105015, <https://doi.org/10.1088/1674-4527/acf18e>.
 22. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records.”
 24. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis*.
 25. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis*.
 26. Ibid.

27. J. D. McLean, C. R. de Freitas, and R. M. Carter, “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
28. Ka-Kit Tung and Jiansong Zhou, “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
29. Petr Chylek et al., “The Role of Atlantic Multi-Decadal Oscillation in the Global Mean Temperature Variability,” *Climate Dynamics* 47, no. 9–10 (February 20, 2016): 3271–3279, <https://doi.org/10.1007/s00382-016-3025-7>.
30. Nicola Scafetta, “Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature,” *Atmosphere* 12, no. 2 (2021): 147, <https://doi.org/10.3390/atmos12020147>.
31. Ross McKittrick, “Checking for Model Consistency in Optimal Fingerprinting: A Comment,” *Climate Dynamics* 58, no. 1–2 (2022): 405–411, <https://doi.org/10.1007/s00382-021-05913-7>.
32. M. R. Allen and S. F. B. Tett, “Checking for Model Consistency in Optimal Fingerprinting,” *Climate Dynamics* 15, no. 6 (1999): 419–434, <https://doi.org/10.1007/s003820050291>.
33. Ross McKittrick, Timothy Vogelsang, and John Christy, “Temperature Trends, Climate Attribution and the Nonstationarity Question,” *Earth System Dynamics Discussions* (2023): <https://doi.org/10.5194/esd-2023-11>.
34. Ross McKittrick, “Total Least Squares Bias in Climate Fingerprinting Regressions with Heterogeneous Noise Variances and Correlated Explanatory Variables,” *Environmetrics* 35, no. 2 (March 2024): e2835, <https://doi.org/10.1002/env.2835>.
35. S. Seneviratne et al., “Chapter 11: Weather and Climate Extreme Events in a Changing Climate.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
36. R. Ranasinghe et al., “Chapter 12: Climate Change Information for Regional Impact and for Risk Assessment.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1767–1926. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.014>.
37. National Academies of Sciences, Engineering, and Medicine. *Attribution of Extreme Weather and Climate Events and Their Impacts*. Washington, DC: The National Academies Press, forthcoming. <https://www.nationalacademies.org/our-work/attribution-of-extreme-weather-and-climate-events-and-their-impacts>.
38. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021: Synoptic/Mesoscale Conditions and Climate Perspective,” *Weather and Forecasting* 39, no. 2 (February 2024): 275–291, <https://doi.org/10.1175/WAF-D-23-0154.1>.
39. World Weather Attribution. “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
40. S.Y. Philip et al., “Rapid Attribution Analysis of the Extraordinary Heatwave on the Pacific Coast of the US and Canada June 2021,” *Earth System Dynamics* 13, no. 4 (December 8, 2022): 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>.

41. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021.”
42. Emily Bercos-Hickey et al., “Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave,” *Geophysical Research Letters* 49, no. 23 (December 2022): e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
43. Judea Pearl, *Causality* (Cambridge: Cambridge University Press, 2009).
44. Geert Jan van Oldenborgh et al., “Attributing and Projecting Heatwaves Is Hard: We Can Do Better,” *Earth’s Future* 10, no. 6 (June 2022): e2021EF002271, <https://doi.org/10.1029/2021EF002271>.
45. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming,” NOAA Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division, 2017, <https://www.aoml.noaa.gov/hrd/Landsea/harvey-global-warming.pdf>.
46. David M. Roth, “Tropical Cyclone Rainfall for the North Atlantic Basin,” Weather Prediction Center, National Oceanic and Atmospheric Administration, 2017, <https://www.wpc.ncep.noaa.gov/tropical/rain/tcmaxima.html>.
47. Geert Jan van Oldenborgh et al., “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017,” *Environmental Research Letters* 12, no. 12 (December 2017): 124009, <https://doi.org/10.1088/1748-9326/aa9ef2>.
48. Kerry Emanuel, “Assessing the Present and Future Probability of Hurricane Harvey’s Rainfall,” *Proceedings of the National Academy of Sciences* 114, no. 48 (November 28, 2017): 12681–12684, <https://doi.org/10.1073/pnas.1716222114>.
49. Mark D. Risser and Michael F. Wehner, “Attributable Human-Induced Changes in the Likelihood and Magnitude of the Observed Extreme Precipitation During Hurricane Harvey,” *Geophysical Research Letters* 44, no. 24 (December 2017): 12,457–12,464, <https://doi.org/10.1002/2017GL075888>.
50. Kevin E. Trenberth et al., “Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation,” *Earth’s Future* 6, no. 5 (May 2018): 730–744, <https://doi.org/10.1029/2018EF000825>.
51. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming.”
52. Yog Aryal et al., “Long Term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño–Southern Oscillation,” *Journal of Hydrology* 559 (2018): 698–710, <https://doi.org/10.1016/j.jhydrol.2018.02.072>.

Ranasinghe, R., A.C. Ruane, R. Vautard, N. Arnell, E. Coppola, F.A. Cruz, S. Dessai, A.S. Islam, M. Rahimi, D. Ruiz Carrascal, J. Sillmann, M.B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul, (2021): Climate Change Information for Regional Impact and for Risk Assessment. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1767–1926, doi:[10.1017/9781009157896.014](https://doi.org/10.1017/9781009157896.014).

- Jones, Gareth, Peter A. Stott and John F.B. Mitchell (2016) Uncertainties in the Attribution of Greenhouse Gas Warming and Implications for Climate Prediction. *Journal of Geophysical Research-Atmospheres* 121(12) 6969—6992 <https://doi.org/10.1002/2015JD024337>.
- Kravtsov, S., A. Westgate and A. Gavrilov (2024) Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics* Volume 62, pages 10281–10306 <https://link.springer.com/article/10.1007/s00382-024-07451-4>
- Weinkle, Jessica (2025) Carnival mirrors: How concentrated is the event attribution literature? Substack essay <https://jessicaweinkle.substack.com/p/how-big-is-the-event-attribution>
- Chen, Chung and Lon-Mu Liu (1993) Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association* Vol. 88, No. 421 (Mar., 1993), pp 284—297. <http://www.jstor.org/stable/2290724>
- Sardeshmukh, Prashant D., Gilbert P. Compo and Cécile Penland (2015) Need for Caution in Interpreting Extreme Weather Statistics *Journal of Climate* 28(23) 9166–9187 <https://journals.ametsoc.org/view/journals/clim/28/23/jcli-d-15-0020.1.xml>
- Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 <https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>
- Miralles, Ophélia and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 <https://doi.org/10.1016/j.wace.2023.100584>
- Barlow, Anna Maria, Chris Sherlock and Jonathan Tawn (2020) Inference for Extreme Values Under Threshold-Based Stopping Rules. *Journal of the Royal Statistical Society Series C* August 2020, Pages 765–789, <https://doi.org/10.1111/rssc.12420>
- Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. <https://doi.org/10.1029/2023GL104090>
- Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. <https://blogs.oregonstate.edu/occri/oregon-climate-assessments> .
- McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophysical Research Letters*, 49, e2022GL100380. <https://doi.org/10.1029/2022GL100380>
- Bercos-Hickey et al. (2022) Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave. *Geophysical Research Letters* 49 <https://doi.org/10.1029/2022GL099396>
- Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay <https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>

12 Climate change, the economy and the Social Cost of Carbon

12.1 Climate change and economic growth

12.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects of climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021).

For these reasons, economists have long been reluctant to endorse attempts to "stop" climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.
(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future 2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus' Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models. (AR6 offers 2.7°C in 2100 under a moderate emissions scenario.)

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we scale back only the lowest-value fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T,

which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

12.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell et al. (2012, herein DJ012) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJ012 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJ012-type results on the same subset of countries as used in DJ012 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJ012 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJ012 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is taken into account the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn't be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response

coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus' earlier analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. The following figure, from a 2023 OMB-CEA [report](#), shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.

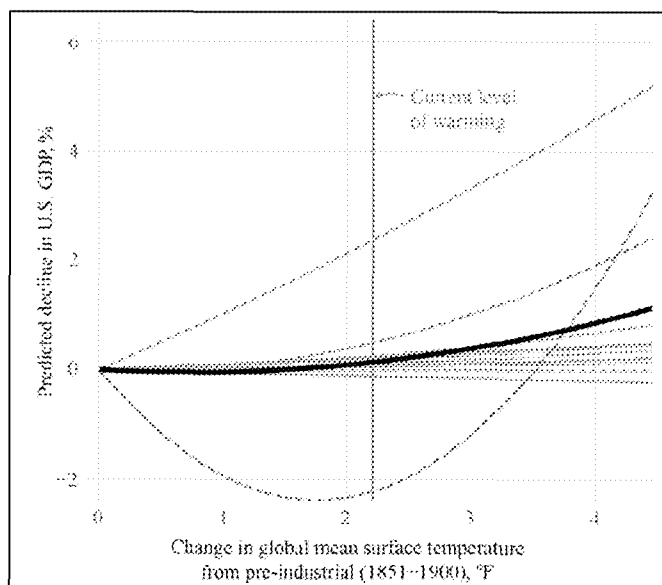


Figure 12.1: Decline in US GDP per degree of warming. Source: XX

12.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

Sidebar: finding the optimal emissions price

On its own the SCC is not the appropriate price to attach to CO₂ emissions for the purpose of optimal emissions control but it can be converted into an optimal tax rate by scaling it by a parameter called the Marginal Cost of Public Funds (MCPF). The theory behind this was first derived by Sandmo (1975) and has been reiterated many times since then by other economists working on the topic (e.g. Parry et al. 1999). The MCPF is the cost in terms of lost private economic welfare of raising public revenue by one dollar and always exceeds unity. If a jurisdiction does not use a carbon tax, this formula still indicates the upper bound on the amount emitters should spend on abatement options at the margin along the optimal policy path. Regulations should be imposed only insofar as they do not impose marginal abatement costs in excess of the optimal tax rate.

12.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying

that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

12.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter 9). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.

- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as discussed in Chapter 10, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

12.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using

updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

12.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz et al. 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen et al. 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are

imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon 2023).

The possible existence of bifurcations in the Earth's climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al 2024) and indeed may not be able to since one implication of the "butterfly effect" is the existence of predictability boundaries of nonlinear systems (Palmer et al. 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the "tipping point" concept in discussions of climate change (see <https://report-2023.global-tipping-points.org/what-is-a-tipping-point/> for example). As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023). It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate "tipping point" is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only a modest increase in the SCC value in the 21st century.

12.3 Summary

In summary, SCC estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions.

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the weaknesses of the SCC concept don't mean that other regulatory measures are inherently better or more efficient. Many climate regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) end up costing far more per tonne of abatement than a simple price on carbon emissions.

Barrage, Lint and William Nordhaus (2024) Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. *Proceedings of the National Academy of Sciences* 121 (13) e2312030121 <https://doi.org/10.1073/pnas.2312030121>

Berg, Kimberly, Chadwick C Curtis and Nelson Mark. (2021) GDP and temperature: Evidence on cross-country response heterogeneity. NBER Working Paper 31327 June 2023 <http://www.nber.org/papers/w31327>

- Chris Thoung (2017) "Is It Time to Kill Off the Social Cost of Carbon?" Cambridge Econometrics Blog, September 14, 2017, <https://www.camecon.com/blog/time-kill-social-cost-carbon/>.
- Daisy Dunne (2017), "Q&A: The Social Cost of Carbon," Carbon Brief, February 14, 2017, <https://www.carbonbrief.org/qa-social-cost-carbon/>
- McKittrick, Ross R. (2025) Extended Crop Yield Meta-analysis Data do not Support Upward SCC Revision. *Scientific Reports* 15 article 5575 <https://www.nature.com/articles/s41598-025-90254-2>
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>
- Nordhaus, W. (1993) Optimal Greenhouse-Gas Reductions and Tax Policy in the "DICE" Model *American Economic Review* Vol. 83, No. 2, (Papers and Proceedings) pp.313-317.
- Parry, Ian, Roberton C. Williams III and Lawrence H. Goulder (1999). "When Can Carbon Abatement Policies Increase Welfare? The Fundamental Role of Distorted Factor Markets." *Journal of Environmental Economics and Management* 37: 52—84.
- Resources for the Future (2025) "Social Cost of Carbon Explorer," Resources for the Future website, accessed April 22, 2025, <https://www.rff.org/publications/data-tools/scc-explorer/>.
- Roe, Gerard H. and Yoram Bauman (2013) Climate Sensitivity: Should the climate tail wag the policy dog? *Climatic Change* (2013) 117:647–662 DOI 10.1007/s10584-012-0582-6
- Sandmo, Agnar (1975) "Optimal Taxation in the Presence of Externalities." *Swedish Journal of Economics* 77 (1), 86–98.
- Tol, R.S.J. (1997) On the optimal control of carbon dioxide emissions: an application of FUND *Environmental Modeling and Assessment* 2: 151—163.
- Tol, Richard S.J. (2017). "The Private Benefit of Carbon and its Social Cost," Working Paper Series 0717, Department of Economics, University of Sussex Business School. <https://ideas.repec.org/p/sus/susewp/0717.html>
- UK Department for Energy Security and Net Zero (2022). "Carbon Valuation." GOV.UK, last updated April 4, 2022. <https://www.gov.uk/government/collections/carbon-valuation--2>.
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review", EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf accessed February 28, 2024.
- Storm, S (2017) "How the Invisible Hand is Supposed to Adjust the Natural Thermostat: A Guide for the Perplexed." *Science and Engineering Ethics* vol 23: 1307—1331.
- Pielke Jr., Roger (2020) Economic 'normalisation' of disaster losses 1998–2020: a literature review and assessment," *Environmental Hazards*, 2020, pp. 1-19
- Pielke Jr., Roger (2018): Tracking progress on the economic costs of disasters under the indicators of the sustainable development goals, *Environmental Hazards*, DOI: 10.1080/17477891.2018.1540343
- Formetta, Giuseppe and Luc Feyen (2019) Empirical evidence of declining global vulnerability to climate-related hazards. *Global Environmental Change* 57 101920 <https://doi.org/10.1016/j.gloenvcha.2019.05.004>
- Hu, Bin and Ross McKittrick (2015) Climatic Variations and the Market Value of Insurance Firms. *Journal of Insurance Issues* Vol. 39, No. 1, pp. 92-111 <https://www.jstor.org/stable/43741103>
- Blickle, Kristian; Sarah N. Hamerling, and Donald P. Morgan (2021) : How bad are weather disasters for banks?, Staff Reports, No. 990, Federal Reserve Bank of New York, New York, NY <https://www.econstor.eu/bitstream/10419/247913/1/sr990.pdf>

Lavelle, Marianne (2019) Carbon Tax Plans: How They Compare and Why Oil Giants Support One of Them. *Inside Climate News* March 7, 2019 <https://insideclimatenews.org/news/07032019/carbon-tax-proposals-compare-baker-shultz-exxon-conocophillips-ccl-congress/>

Dietz, S., J. Rising, T. Stoerk, G. Wagner (2021) Economic impact of tipping points in the climate system. *PNAS* 2021 Vol. 118 No. 34 e2103081118

Shen, Bo-Wen, Roger A Pielke Sr and Xubin Zeng (2023) The 50th Anniversary of the Metaphorical Butterfly Effect since Lorenz (1972): Multistability, Multiscale Predictability, and Sensitivity in Numerical Models. *Atmosphere* 2023 14(8) <https://doi.org/10.3390/atmos14081279>

Crawford, John D (1991) Introduction to Bifurcation Theory. *Reviews of Modern Physics* 63(4) October 1991 991—1037.

Kypke, K. L., Langford, W. F., and Willms, A. R.: Anthropocene climate bifurcation, *Nonlin. Processes Geophys.*, 27, 391–409, <https://doi.org/10.5194/npg-27-391-2020>, 2020.

Brunetti, Maura and Charline Ragon (2023) Attractors and bifurcation diagrams in complex climate models. *Physical Review E* 107 054214 <https://journals.aps.org/pre/abstract/10.1103/PhysRevE.107.054214>

Dakos, Vasilis, Chris Boulton, Joshua Buxton et al. (2024) Tipping point detection and early warnings in climate, ecological, and human systems. *Earth System Dynamics* 15 1117—1135 <https://doi.org/10.5194/esd-15-1117-2024>

Palmer, TN, A Döring and G Seregin (2014) The real butterfly effect. *Nonlinearity* 27(9) 10.1088/0951-7715/27/9/R123 <https://iopscience.iop.org/article/10.1088/0951-7715/27/9/R123/meta>

Lenton, T.M., D.I. Armstrong McKay, S. Loriani, J.F. Abrams, S.J. Lade, J.F. Donges, M. Milkoreit, T. Powell, S.R. Smith, C. Zimm, J.E. Buxton, E. Bailey, L. Laybourn, A. Ghadiali, J.G. Dyke (eds), 2023, *The Global Tipping Points Report 2023*. University of Exeter, Exeter, UK.

12.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz et al. 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen et al. 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily depend on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon 2023).

The possible existence of bifurcations in the Earth’s climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al 2024) and indeed may not be able to since one implication of the “butterfly effect” is the existence of predictability boundaries of nonlinear systems (Palmer et a. 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the “tipping point”

concept in discussions of climate change (see <https://report-2023.global-tipping-points.org/what-is-a-tipping-point/> for example). As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by The Global Tipping Points Report that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023) <https://report-2023.global-tipping-points.org>. It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate “tipping point” is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only

a modest increase in the SCC value in the 21st century.

Dietz, S., J. Rising, T. Stoerk, G. Wagner (2021) Economic impact of tipping points in the climate system. *PNAS* 2021 Vol. 118 No. 34 e2103081118

Shen, Bo-Wen, Roger A Pielke Sr and Xubin Zeng (2023) The 50th Anniversary of the Metaphorical Butterfly Effect since Lorenz (1972): Multistability, Multiscale Predictability, and Sensitivity in Numerical Models. *Atmosphere* 2023 14(8) <https://doi.org/10.3390/atmos14081279>

Crawford, John D (1991) Introduction to Bifurcation Theory. *Reviews of Modern Physics* 63(4) October 1991 991—1037.

Kypke, K. L., Langford, W. F., and Willms, A. R.: Anthropocene climate bifurcation, *Nonlin. Processes Geophys.*, 27, 391–409, <https://doi.org/10.5194/npg-27-391-2020>, 2020.

Brunetti, Maura and Charline Ragon (2023) Attractors and bifurcation diagrams in complex climate models. *Physical Review E* 107 054214
<https://journals.aps.org/pre/abstract/10.1103/PhysRevE.107.054214>

Dakos, Vasilis, Chris Boulton, Joshua Buxton et al. (2024) Tipping point detection and early warnings in climate, ecological, and human systems. *Earth System Dynamics* 15 1117—1135
<https://doi.org/10.5194/esd-15-1117-2024>

Palmer, TN, A Döring and G Seregin (2014) The real butterfly effect. *Nonlinearity* 27(9) 10.1088/0951-7715/27/9/R123 <https://iopscience.iop.org/article/10.1088/0951-7715/27/9/R123/meta>

Declining planetary albedo and recent record warmth

Planetary albedo is the fraction of incoming solar radiation that is reflected back into space by reflective surfaces like cloud tops and snow, rather than being absorbed at the surface. Earth's planetary albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed at the surface to be then re-radiated as heat into the atmosphere. Hence, other things being equal, a decline in Earth's albedo is associated with a warming of the atmosphere.

Arguably the most striking change to the Earth's climate system in the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure xxx shows the planetary albedo variations since 2000, when we have good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in solar energy averaged over the planet (Hansen and Karecha, 2025). For reference, doubling of CO₂ has a direct radiative impact of about 1.2 W/m².

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before industrial aerosol precursor emissions led to global dimming until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

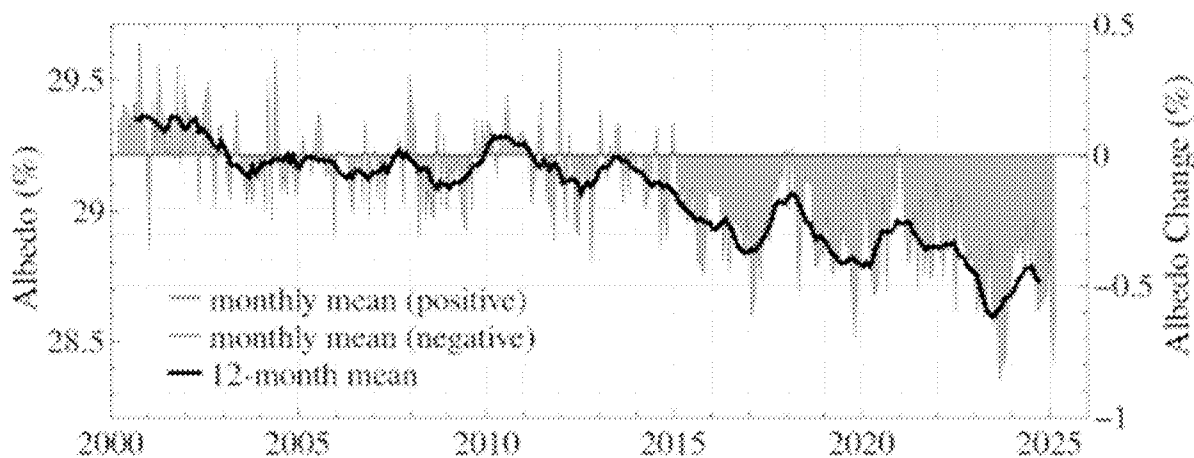


Figure xxx. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can't explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al., 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (SPM, A.1.5)
- Northern hemispheric snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer.
<http://climate.rutgers.edu/snowcover/>

- Global greening (Chapter 2) is contributing the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as being caused by changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. In terms of pollution aerosol, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the northern hemisphere, whereas in the southern hemisphere the decrease in planetary albedo is primarily from decreases in mid-level clouds across all latitude zones. Gossling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Nino event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019

- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Nino Southern Oscillation (ENSO), which have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

References

35. S. A. Klein, A. Hall, J. R. Norris, R. Pincus, Low-cloud feedbacks from cloud-controlling factors: A review. *Surv Geophys* 38,1307-1329 (2017). doi:10.1007/s10712-017-9433-3
48. C. L. Boehm, D. W. J. Thompson, The Key Role of Cloud–Climate Coupling in Extratropical Sea Surface Tempe
- K. Li, F. Zheng, J. Zhu, Q.-C. Zeng, El Niño and the AMO Sparked the Astonishingly Large Margin of Warming in the Global Mean Surface Temperature in 2023. *Adv. Atmos. Sci.* 41, 1017-1022 (2024). doi:10.1007/s00376-023-3371-4

References

N. G. Loeb et al., Decomposing Shortwave Top-of-Atmosphere and Surface Radiative Flux Variations in Terms of Surface and Atmospheric Contributions. *Journal of Climate* 32(16), 5003-5019 (2019). doi:10.1175/JCLI-D-18-0826.1

G. Schmidt, Climate models can't explain 2023's huge heat anomaly — we could be in uncharted territory. *Nature* 627, 467 (2024).

Ø. Hodnebrog et al., Recent reductions in aerosol emissions have increased Earth's energy imbalance. *Commun Earth Environ* 5, 166 (2024). doi:10.1038/s43247-024-01324-8

13. T. Yuan, et al., Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Commun Earth Environ* 5, 281 (2024). doi:10.1038/s43247-024-01442-3

Mark England, Lorenzo M Polvani, James A Screen, et al. Surprising, but not unexpected, multi-decadal pause in Arctic sea ice loss. *ESS Open Archive* . March 29, 2025.

Hansen J and P Karecha (2025) Large cloud feedback confirms high sensitivity
<https://mailchi.mp/caa/large-cloud-feedback-confirms-high-climate-sensitivity>

G. Schmidt, Climate models can't explain 2023's huge heat anomaly — we could be in uncharted territory. *Nature* 627, 467 (2024).

Ø. Hodnebrog et al., Recent reductions in aerosol emissions have increased Earth's energy imbalance. *Commun Earth Environ* 5, 166 (2024). doi:10.1038/s43247-024-01324-8

13. T. Yuan, et al., Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Commun Earth Environ* 5, 281 (2024). doi:10.1038/s43247-024-01442-3

Loeb, N., S-H Ham, RP Allen, TJ Thorsen, B Meyssignac, S Kato, GC Johnson, JL Lyman,(2024) Observational Assessment of Changes in Earth's Energy Budget since 2000. *Surveys in Geophysics*, 45, 1757-1783

Desbruyeres, D, L Chafik and G Maze (2021) A shift in the ocean circulation has warmed the subpolar North Atlantic Ocean since 2016. *Communications Earth&Environment*.

Arthun, M, RCJ Willis, HL Johnson, L Chafik, HR Langehaug (2021) Mechanisms of Decadal North Atlantic Climate Variability and Implications for the Recent Cold Anomaly. *Journal of Climate*, Vol 34

Kuchar, A., Sukhodolov, T., Chiodo, G., Jörimann, A., Kult-Herdin, J., Rozanov, E., and Rieder, H. H.: Modulation of the northern polar vortex by the Hunga Tonga–Hunga Ha'apai eruption and the associated surface response, *Atmos. Chem. Phys.*, 25, 3623–3634, <https://doi.org/10.5194/acp-25-3623-2025>, 2025.

Bednarz, EW, AH Butler, X Wang, Z Zhou, W Yu, G Stenchikov, M Toohey, Y Zhu (2025) Indirect climate impacts of the Hunga eruption. Preprint, <https://doi.org/10.5194/egusphere-2025-1970>

Kuchar, A., Sukhodolov, T., Chiodo, G., Jörimann, A., Kult-Herdin, J., Rozanov, E., and Rieder, H. H.: Modulation of the northern polar vortex by the Hunga Tonga–Hunga Ha'apai eruption and the associated surface response, *Atmos. Chem. Phys.*, 25, 3623–3634, <https://doi.org/10.5194/acp-25-3623-2025>, 2025.

identify a decadal mode of atmosphere–ocean variability in the North Atlantic with a dominant time scale of 13–18 years. Large-scale atmospheric circulation anomalies drive SST anomalies both through contemporaneous air–sea heat fluxes and through delayed ocean circulation changes, the latter involving both the meridional overturning circulation and the horizontal gyre circulation.

Declining planetary albedo and recent record warmth

Planetary albedo is the fraction of incoming solar radiation that is reflected back into space by the Earth's surface and atmosphere. Earth's planetary albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is reflected back to space.

Arguably the most striking change to the Earth's climate system in the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure xxx shows the planetary albedo variations since 2000, when we have good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in solar energy averaged over the planet (Hansen and Karecha, 2025). For reference, doubling of CO₂ has a direct radiative impact of about 1.2 W/m².

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before industrial aerosol precursor emissions led to global dimming until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

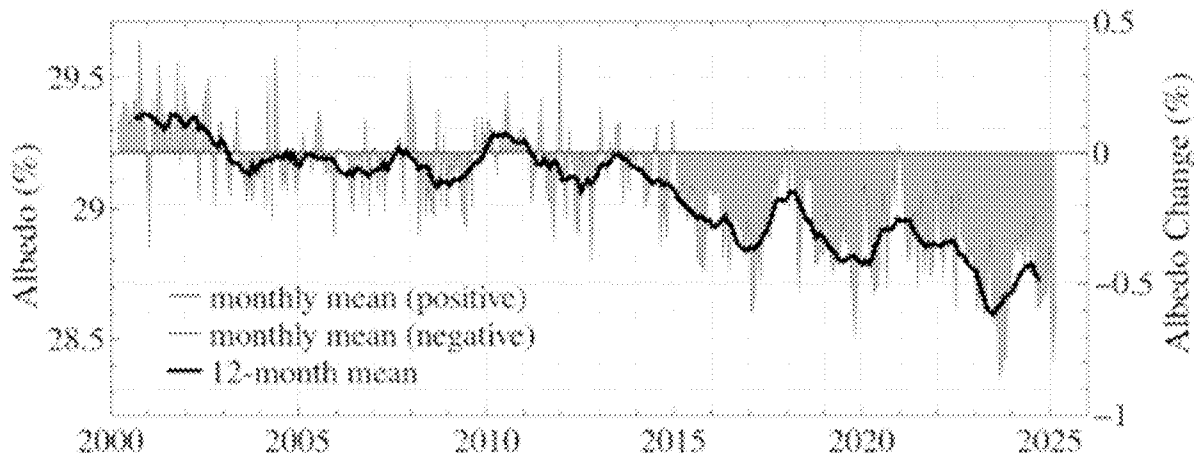


Figure xxx. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can't explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al., 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (SPM, A.1.5)
- Northern hemispheric snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer. <http://climate.rutgers.edu/snowcover/>
- Global greening (Chapter 2) is contributing the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase

cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as being caused by changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. In terms of pollution aerosol, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the northern hemisphere, whereas in the southern hemisphere the decrease in planetary albedo is primarily from decreases in mid-level clouds across all latitude zones. Gossling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Nino event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO), which have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

References

- 35. S. A. Klein, A. Hall, J. R. Norris, R. Pincus, Low-cloud feedbacks from cloud-controlling factors: A review. *Surv Geophys* 38,1307-1329 (2017). doi:10.1007/s10712-017-9433-3
- 48. C. L. Boehm, D. W. J. Thompson, The Key Role of Cloud–Climate Coupling in Extratropical Sea Surface Temperature
- K. Li, F. Zheng, J. Zhu, Q.-C. Zeng, El Niño and the AMO Sparked the Astonishingly Large Margin of Warming in the Global Mean Surface Temperature in 2023. *Adv. Atmos. Sci.* 41, 1017-1022 (2024). doi:10.1007/s00376-023-3371-4

References

N. G. Loeb et al., Decomposing Shortwave Top-of-Atmosphere and Surface Radiative Flux Variations in Terms of Surface and Atmospheric Contributions. *Journal of Climate* 32(16), 5003-5019 (2019). doi:10.1175/JCLI-D-18-0826.1

G. Schmidt, Climate models can't explain 2023's huge heat anomaly — we could be in uncharted territory. *Nature* 627, 467 (2024).

Ø. Hodnebrog et al., Recent reductions in aerosol emissions have increased Earth's energy imbalance. *Commun Earth Environ* 5, 166 (2024). doi:10.1038/s43247-024-01324-8

13. T. Yuan, et al., Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Commun Earth Environ* 5, 281 (2024). doi:10.1038/s43247-024-01442-3

Mark England, Lorenzo M Polvani, James A Screen, et al. Surprising, but not unexpected, multi-decadal pause in Arctic sea ice loss. *ESS Open Archive* . March 29, 2025.

Hansen J and P Karecha (2025) Large cloud feedback confirms high sensitivity
<https://mailchi.mp/caa/large-cloud-feedback-confirms-high-climate-sensitivity>

G. Schmidt, Climate models can't explain 2023's huge heat anomaly — we could be in uncharted territory. *Nature* 627, 467 (2024).

Ø. Hodnebrog et al., Recent reductions in aerosol emissions have increased Earth's energy imbalance. *Commun Earth Environ* 5, 166 (2024). doi:10.1038/s43247-024-01324-8

13. T. Yuan, et al., Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Commun Earth Environ* 5, 281 (2024). doi:10.1038/s43247-024-01442-3

Loeb, N., S-H Ham, RP Allen, TJ Thorsen, B Meyssignac, S Kato, GC Johnson, JL Lyman,(2024) Observational Assessment of Changes in Earth's Energy Budget since 2000. *Surveys in Geophysics*, 45, 1757-1783

Desbruyeres, D, L Chafik and G Maze (2021) A shift in the ocean circulation has warmed the subpolar North Atlantic Ocean since 2016. *Communications Earth&Environment*.

Arthun, M, RCJ Willis, HL Johnson, L Chafik, HR Langehaug (2021) Mechanisms of Decadal North Atlantic Climate Variability and Implications for the Recent Cold Anomaly. *Journal of Climate*, Vol 34

Kuchar, A., Sukhodolov, T., Chiodo, G., Jörimann, A., Kult-Herdin, J., Rozanov, E., and Rieder, H. H.: Modulation of the northern polar vortex by the Hunga Tonga–Hunga Ha'apai eruption and the associated surface response, *Atmos. Chem. Phys.*, 25, 3623–3634, <https://doi.org/10.5194/acp-25-3623-2025>, 2025.

Bednarz, EW, AH Butler, X Wang, Z Zhou, W Yu, G Stenchikov, M Toohey, Y Zhu (2025) Indirect climate impacts of the Hunga eruption. Preprint, <https://doi.org/10.5194/egusphere-2025-1970>

Kuchar, A., Sukhodolov, T., Chiodo, G., Jörimann, A., Kult-Herdin, J., Rozanov, E., and Rieder, H. H.: Modulation of the northern polar vortex by the Hunga Tonga–Hunga Ha'apai eruption and the associated surface response, *Atmos. Chem. Phys.*, 25, 3623–3634, <https://doi.org/10.5194/acp-25-3623-2025>, 2025.

identify a decadal mode of atmosphere–ocean variability in the North Atlantic with a dominant time scale of 13–18 years. Large-scale atmospheric circulation anomalies drive SST anomalies both through contemporaneous air–sea heat fluxes and through delayed ocean circulation changes, the latter involving both the meridional overturning circulation and the horizontal gyre circulation.



An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America

Climate Science Research Team
United States Department of Energy
May 24, 2025

An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America

Prepared for Secretary Christopher Wright
May 24, 2025

Climate Science Research Team:

John Christy, Ph.D.
Judith Curry, Ph.D.
Steven Koonin, Ph.D.
Ross McKittrick, Ph.D.
Roy Spencer, Ph.D.

Copyright © 2025 United States

Suggested citation:

Christy, John, Judith Curry, Steven Koonin, Ross McKittrick and Roy Spencer (2025) *An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States of America*. Report of the Climate Science Research Team, Washington DC: Department of Energy, May 24 2025.

Table of Contents

Preface

Comments by Secretary Wright

Foreword

This document originated in late March 2025 when Secretary Wright assembled an independent team to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the US public. The team agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The team began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. While the report is intended to be accessible for non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere.

While the team writing this report was aware that the Administration was undertaking a reconsideration of the 2009 Endangerment Finding we were not involved in, nor briefed on, the specifics of that process. Our report is submitted in the expectation that it will help inform that effort.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support for independent scientific inquiry.

Part I

Direct human influence on
ecosystems and the climate

1 Carbon dioxide as pollutant

In 2006, the Supreme Court ruled that GHGs (CO₂ among them) were “pollutants” subject to regulation under Clean Air Act (Mass. V. EPA 2006). That framework defines six types of so-called Criteria Air Contaminants (EPA, undated): particulate matter, ground-level ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and carbon monoxide (CO).

While the definition of “pollutant” is ultimately a legal one, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation. In these aspects, it is similar to water.

Ambient outdoor air today contains about 420 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen *et al.* (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and also by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG), that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

References:

- Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. *Environmental Health Perspectives* 124(6) pp. 805-812
<https://doi.org/10.1289/ehp.1510037>
- Massachusetts v. EPA (2006) <https://www.oyez.org/cases/2006/05-1120>
- US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.
- US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

2 Direct Impacts of CO₂ on the environment

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

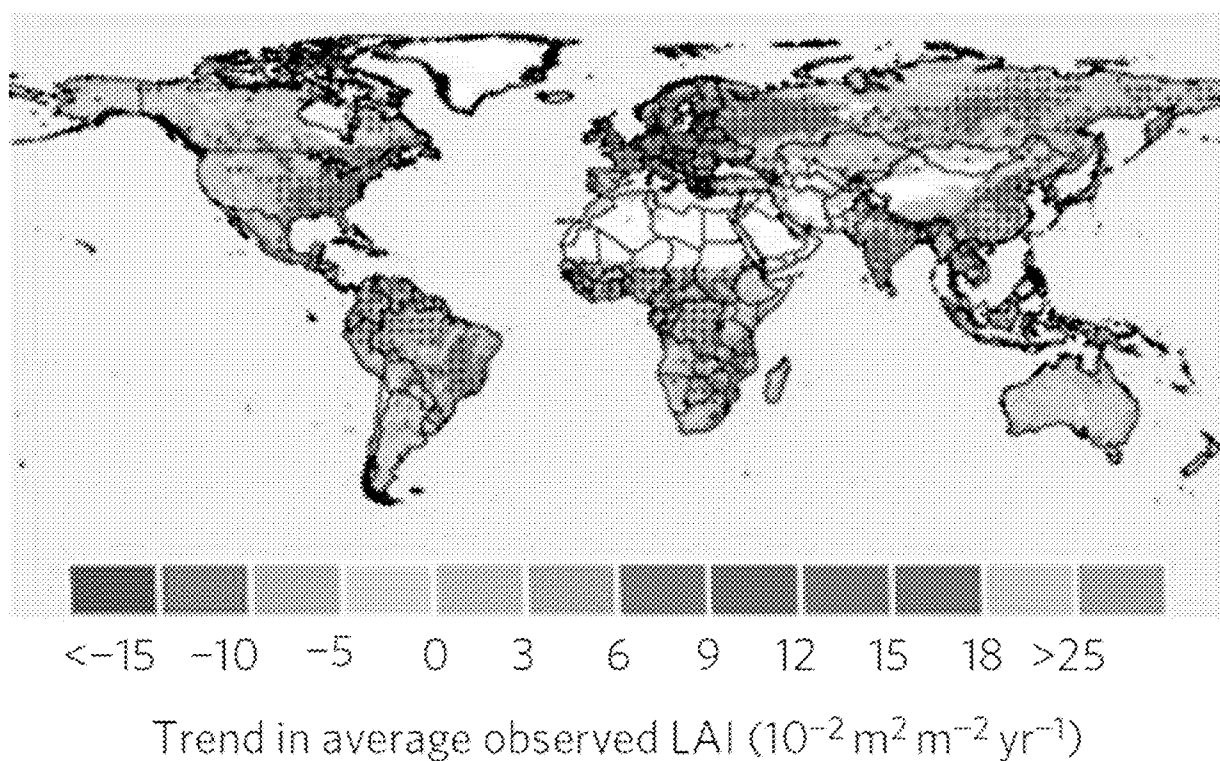


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al.

(2019) noted that China and India were exploiting it through land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

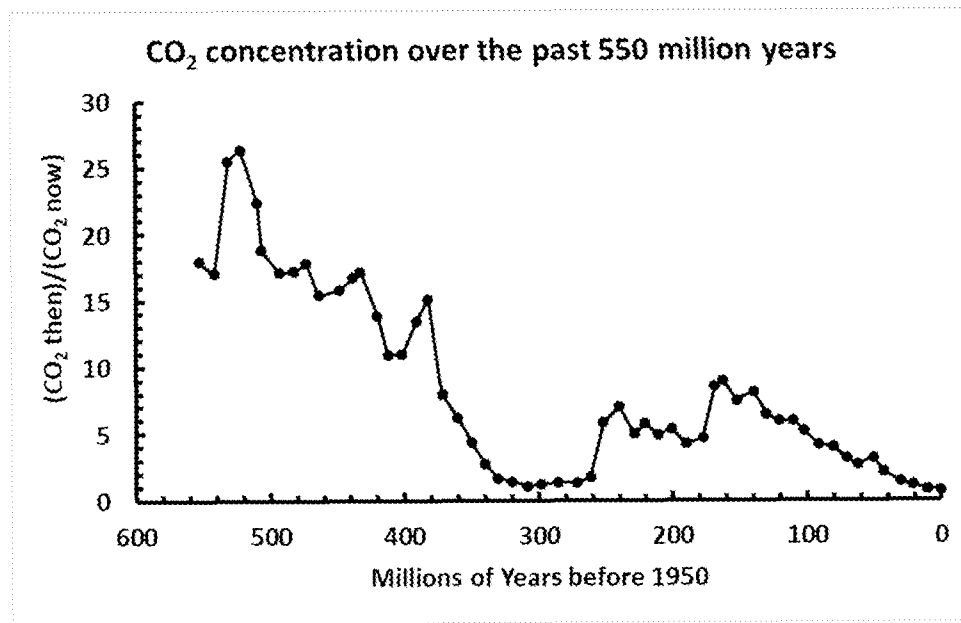


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels. Source: Adapted from Berner (2006). Current CO₂ levels correspond to about 1.3 times the indicated value at 0.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

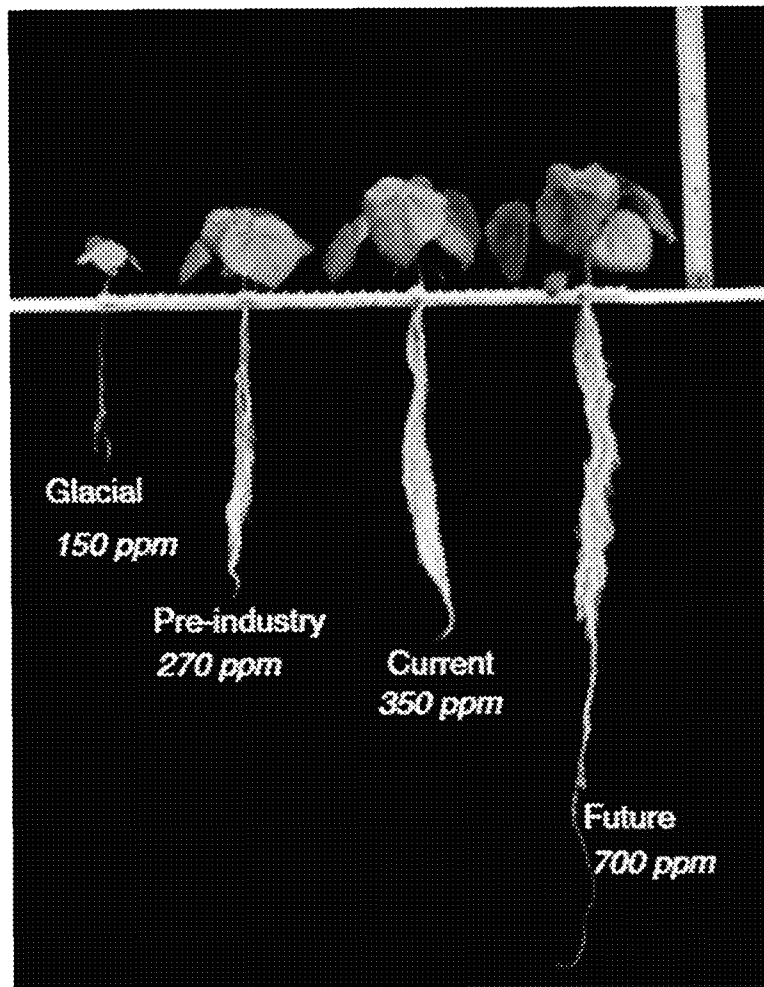


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 Concealment of CO₂ fertilization benefits in IPCC Summaries

The greening topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

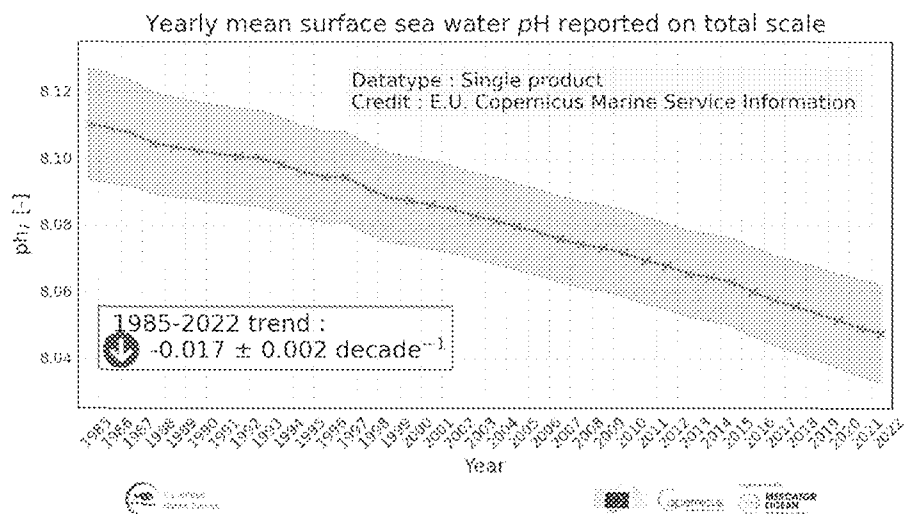


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given

the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

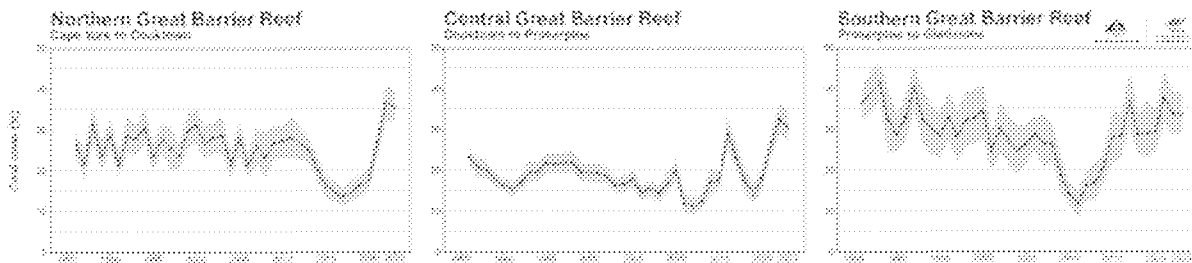


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

2.2.3 Publication bias

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An *ICES Journal of Marine Science* Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.

Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Changes to the Australian Great Barrier Reef are driven by many factors other than temperatures or alkalinity and coral cover has recently staged a major rebound. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

References

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>
- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Australia Institute of Marine Science (2023) AIMS' Annual Summary Report of Coral Reef Condition 2022/23 for the Great Barrier Reef. https://www.aims.gov.au/sites/default/files/2023-08/QuickLook_AIMS_LTMP_Report_GBR_coral_status_22_23.pdf
- Australian Institute of Marine Science (2022). Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef. https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf
- Beeden, R., Maynard, J., Puotinen, M., Marshall, P., Dryden, J., Goldberg, J., and Williams, G. (2015). Impacts and Recovery from Severe Tropical Cyclone Yasi on the Great Barrier Reef. *PLOS ONE*. 10. e0121272. <https://doi.org/10.1371/journal.pone.0121272>
- Berner, R.A. (2006) GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.
- Browman, H. (2016). Applying organized scepticism to ocean acidification research. *iCES Journal of Marine Science: Journal du Conseil*. 73. 529.1-536. <https://doi.org/10.1093/icesjms/fsw010>
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
- Chen, Xin et al. (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791 <https://www.sciencedirect.com/science/article/pii/S2351989423004262>
- Cheng, L., Zhang, L., Wang, YP. et al. Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* 8, 110 (2017). <https://doi.org/10.1038/s41467-017-00114-5>
- Clements JC, Sundin J, Clark TD, Jutfelt F (2022) Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. *PLoS Biol* 20(2): e3001511. <https://doi.org/10.1371/journal.pbio.3001511>
- Copernicus Marine Service (2025) Global Ocean acidification - mean sea water pH time series and trend from Multi-Observations Reprocessing. Online source https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description
- De'ath, G., Lough, J., and Fabricius, K. (2009). Declining Coral Calcification on the Great Barrier Reef. *Science* (New York, N.Y.). 323. 116-9. <https://doi.org/10.1126/science.1165283>
- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 18 April 2016 DOI: 10.1038/NCLIMATE2995.
- Gattuso, J. P. and Hansson, L. (2011). Ocean acidification: background and history Ocean Acidification ed J P Gattuso and L Hansson (Oxford: Oxford University Press).
- Gerhart, Laci and Joy Ward (2010) Plant responses to low [CO₂] of the past. *New Phytologist* 188:674–695. <https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>

- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* 26: 2390–2402.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, 764, 142797.
- Judd, Emily et al. (2024) A 485-million-year history of Earth's surface temperature. *Science* 385 Issue 6715 <https://doi.org/10.1126/science.adk3705>
- Krissansen-Totton, J., Arney, G., and Catling, D. (2018). Constraining the climate and ocean pH of the early Earth with a geological carbon cycle model. *Proceedings of the National Academy of Sciences*. 115. 201721296. <https://doi.org/10.1073/pnas.1721296115>
- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, 15(10), e0241081.
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105-112.
- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, 112, 125961.
- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* 1:14-27
- Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO₂ storage and release in the deep Southern Ocean on millennial to centennial timescales. *Nature*. 562. <https://doi.org/10.1038/s41586-018-0614-0>
- Revelle, R. R. and R. Fairbridge (1957). Carbonate and carbon dioxide, in *Treatise on Marine. Ecology and Paleocology*, Vol. 1: J. W. Hedgpeth, ed.
- Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. *Marine Geology*. 346. 392–399. <https://doi.org/10.1016/j.margeo.2013.09.002>
- Verhage, F. Y. (2017, November). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. Retrieved October 2024, from esalq: http://www.esalq.usp.br/departamentos/leeb/eventos/Thesis_Report_-_Fabian_Verhage.pdf
- Woods Hole Oceanographic Institution (2023). Is the Great Barrier Reef Making a Comeback? <https://www.whoi.edu/oceanus/feature/is-the-great-barrier-reef-making-a-comeback/>
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* 7:432-436 May 2017 <https://www.nature.com/articles/nclimate3299>
- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 <https://www.nature.com/articles/s43247-024-01463-y>
- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* 6 Aug 2016 <https://www.nature.com/articles/nclimate3004>

3 Human influences on the climate

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to space. Averaged over the Earth's surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

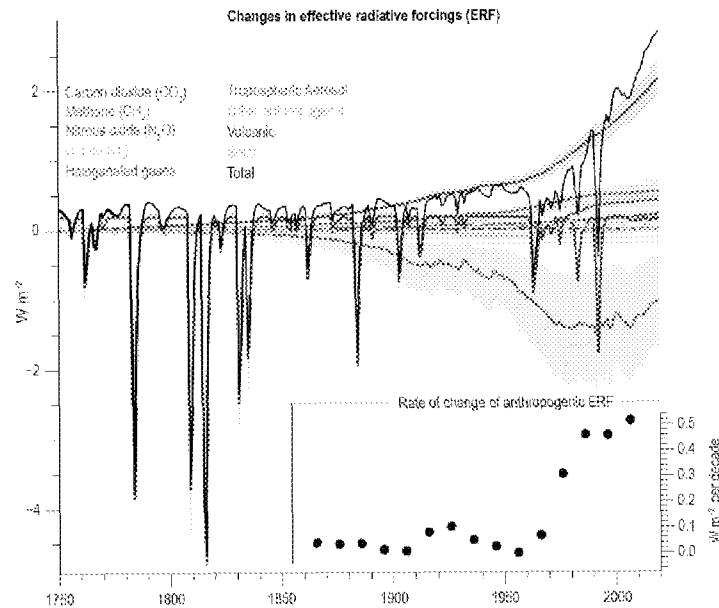


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

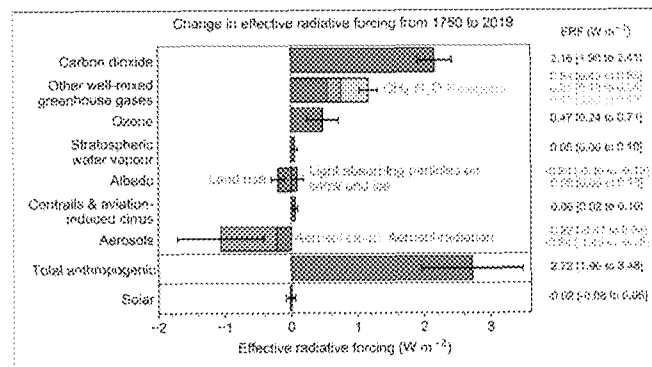


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the

1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how that gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024).

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

3.1.2 Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration above 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

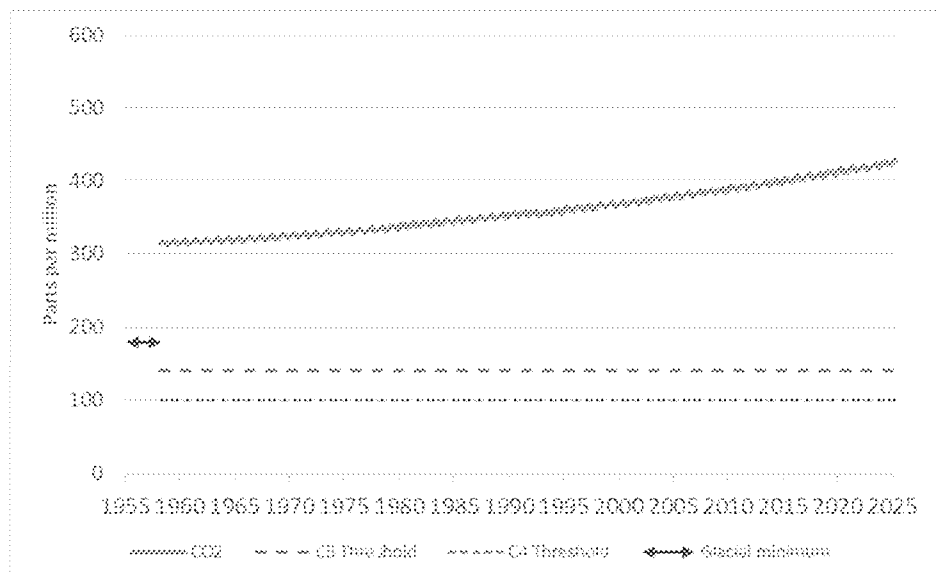


Fig. 3.1.3 CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow).

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts, they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles (p. 16) linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking below SSP2-5.

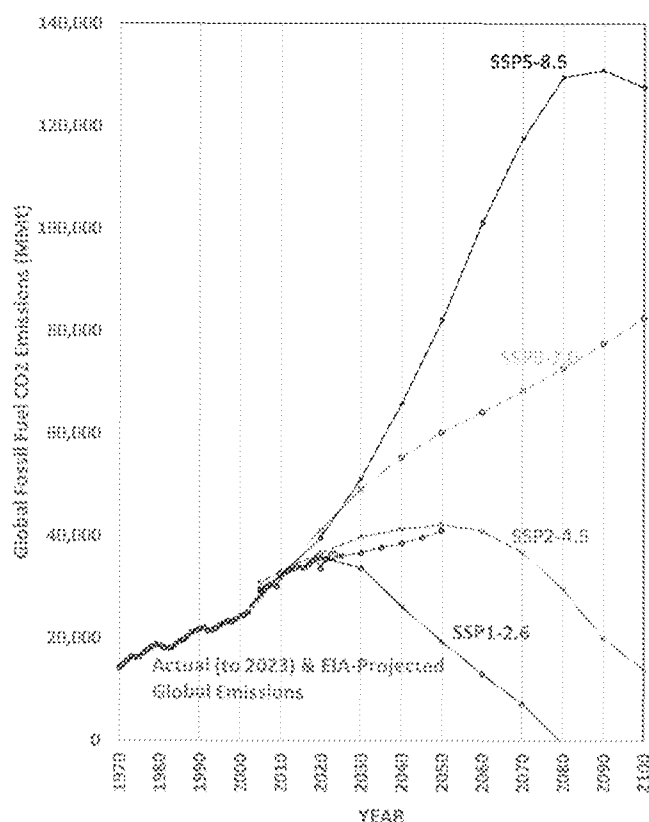


Figure 3.2.1. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth’s surface are an order of magnitude larger than anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013). As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 2.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small - when emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since carbon cycle is vast and slow. A change in local emissions today will have only a very small global effect, and even that only with a long delay. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently, it will take decades or centuries for U.S. CO₂ emission reductions to have a meaningful impact on the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up being too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions have minimal local effects, and only with a long delay. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue. The scale problem is compounded by recognizing that U.S. motor vehicles account only for about 4 percent of global CO₂ emissions so that even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

In summary, the global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere. The IPCC has downplayed the role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it might have been important, and the modern record is uncertain due to an interruption in satellite coverage. IPCC emission scenarios have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading. Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice. The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Hence even global-scale emission reductions will have only small, much delayed effects.

References

- Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>
- Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>
- Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>
- Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

- Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129, <https://doi.org/10.1029/2024JD041296>
- Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>
- Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

NEED TO INSERT OTHER REFERENCES

4 Climate Sensitivity to CO₂ Forcing

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and so also the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney et al. 1979) proposed that the most likely ECS was $3.0 \pm 1.5^{\circ}\text{C}$. The IPCC repeatedly reaffirmed the range with only minor variations until its most recent AR6. AR5 termed $1.5 - 4.5^{\circ}\text{C}$ as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C .

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to $2.5-4.0^{\circ}\text{C}$ and deemed the *very likely* range to be $2.0 - 5.0^{\circ}\text{C}$. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0°C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based methods of computing climate sensitivity to GHGs

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 5.1). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by GCMs, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

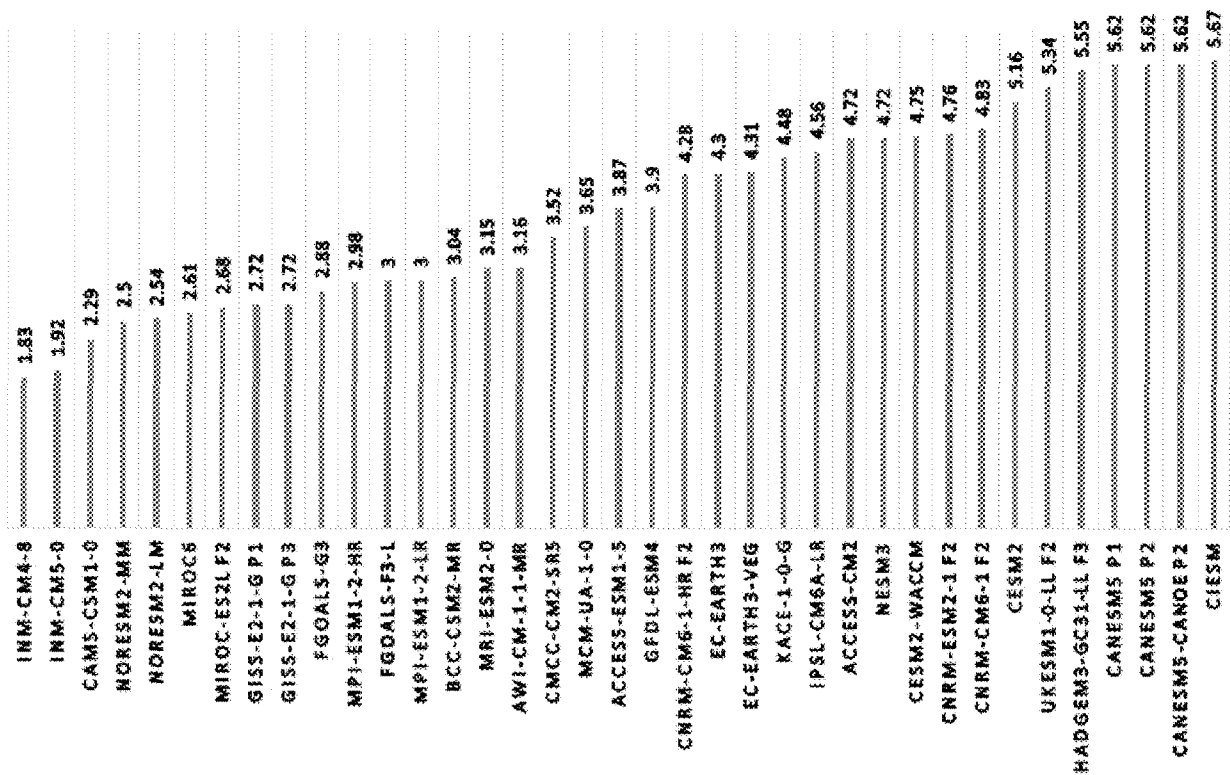


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

4.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil

fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”
Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in

climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

4.4 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS below the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

4.5 Summary

In the past 5 years, there is a growing realization that climate models (GCMs) are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to poorly resolved processes related to clouds and water vapor. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

References

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems* 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

1. Lan, X., Tans, P. and K.W. Thoning: Trends in globally-averaged CO₂ determined from NOAA Global Monitoring Laboratory measurements. Version Monday, 14-Apr-2025 09:08:57 MDT
<https://doi.org/10.15138/9N0H-ZH07>.
2. Zeke Hausfather, "Explainer: How Scientists Estimate Climate Sensitivity," *Carbon Brief*, July 22, 2020, <https://www.carbonbrief.org/explainer-how-scientists-estimate-climate-sensitivity>.
3. Jule Charney et al., "Carbon Dioxide and Climate: A Scientific Assessment," 1979, <https://doi.org/10.17226/12181>.
4. Rajendra K. Pachauri and Leo Meyer, *Climate Change 2014: Synthesis Report* (Geneva, CH: Intergovernmental panel on climate change, 2015).
5. "In-Depth Q&A: The IPCC's Sixth Assessment Report on Climate Science," Carbon Brief, August 9, 2021, <https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-report-on-climate-science>.
6. Nicola Scafetta, "Testing the CMIP6 GCM Simulations versus Surface Temperature Records from 1980–1990 to 2011–2021: High ECS Is Not Supported," *Climate* 9, no. 11 (2021): 161, <https://doi.org/10.3390/cli9110161>.
7. Brian J. Soden and Isaac M. Held, "An Assessment of Climate Feedbacks in Coupled Ocean–Atmosphere Models," *Journal of Climate* 19, no. 14 (July 15, 2006): 3354–3360, <https://doi.org/10.1175/jcli3799.1>.
8. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence," *Reviews of Geophysics* 58, no. 4 (July 22, 2020), <https://doi.org/10.1029/2019rg000678>.
9. Judith A. Curry and Peter J. Webster, "Thermodynamic Feedbacks in the Climate System," in *Thermodynamics of Atmospheres and Oceans* (New York, NY: Academic Press, 1999), 351–385.
10. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
11. D. Chen et al., "Framing, Context, and Methods."
12. Mark D. Zelinka et al., "Causes of Higher Climate Sensitivity in CMIP6 Models," *Geophysical Research Letters* 47, no. 1 (2020): e2019GL085782, <https://doi.org/10.1029/2019GL085782>.
13. Thorsten Mauritsen and Johann Jungclaus, "Tuning the MPI-ESM1.2 Global Climate Model to Improve the Match With Instrumental Record Warming by Lowering Its Climate Sensitivity," *Journal of Advances in Modeling Earth Systems* 12, no. 7 (2020): e2019MS002037, <https://doi.org/10.1029/2019MS002037>.
14. Alexander Otto et al., "Energy Budget Constraints on Climate Response," *Nature Geoscience* 6, no. 6 (May 19, 2013): 415–416, <https://doi.org/10.1038/ngeo1836>.
15. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?" *Atmospheric Chemistry and Physics* 24, no. 5 (2024): 2679–2686, <https://doi.org/10.5194/acp-24-2679-2024>.
16. "Why Low-End 'Climate Sensitivity' Can Now Be Ruled Out," Carbon Brief, July 22, 2020, <https://www.carbonbrief.org/guest-post-why-low-end-climate-sensitivity-can-now-be-ruled-out>.
17. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity."
18. D. Chen et al., "Framing, Context, and Methods."
19. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence," *Climate Dynamics* 61, no. 9–10 (2023): 3155–3163, <https://doi.org/10.1007/s00382-022-06398-8>.
20. Ibid.
21. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?"

22. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)," *EGUsphere* [preprint], 2025, <https://doi.org/10.5194/egusphere-2025-1179>.
23. P. Forster et al., (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V. et al. (eds.)], Cambridge University Press, 2021.
24. Richard Seager et al., "Strengthening Tropical Pacific Zonal Sea Surface Temperature Gradient Consistent with Rising Greenhouse Gases," *Nature Climate Change* 9, no. 7 (2019): 517–522, <https://doi.org/10.1038/s41558-019-0505-x>.
25. Sangyeop Lee et al., "Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint," *Climate Dynamics* 62, no. 1–2 (2024): 229–246, <https://doi.org/10.1007/s00382-023-06741-7>.
26. D. Chen et al., "Framing, Context, and Methods."
27. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
28. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
29. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
30. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)."

Nierenberg, William et al. (1983) *Changing Climate: Report of the Carbon Dioxide Assessment Committee*. Washington, National Academies Press 1983.

2 Direct Impacts of CO₂ on the environment

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

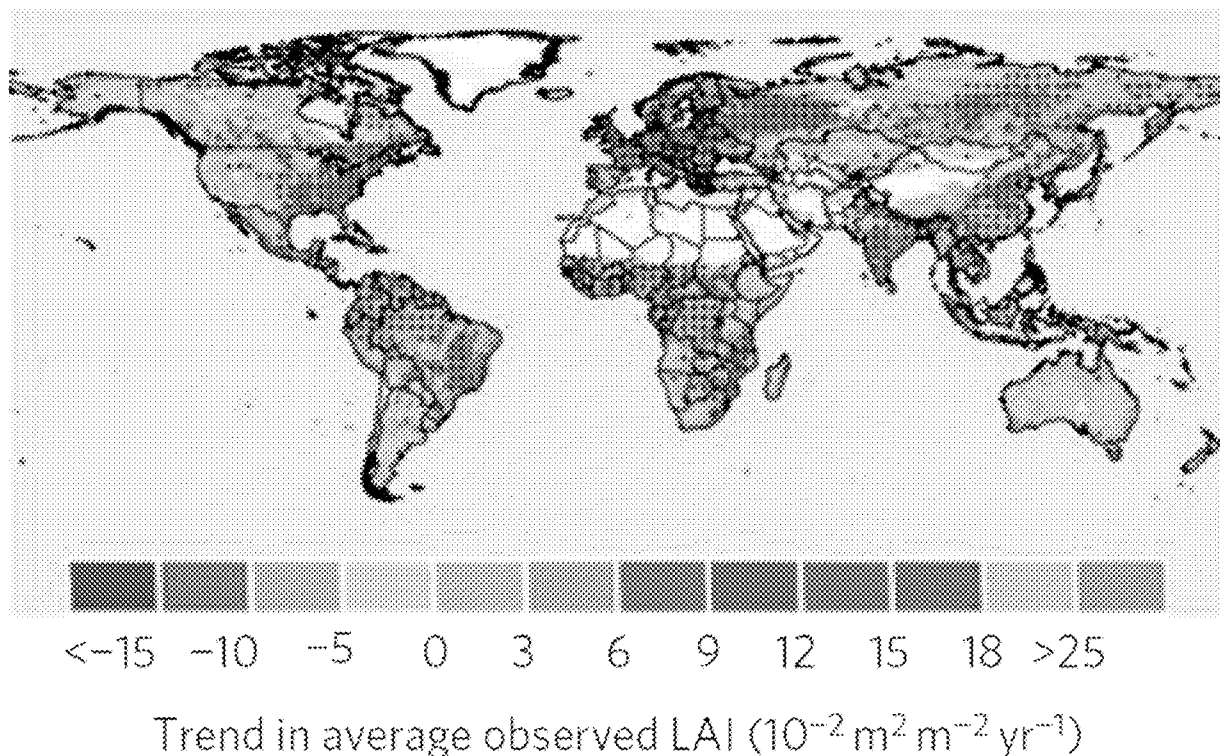


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

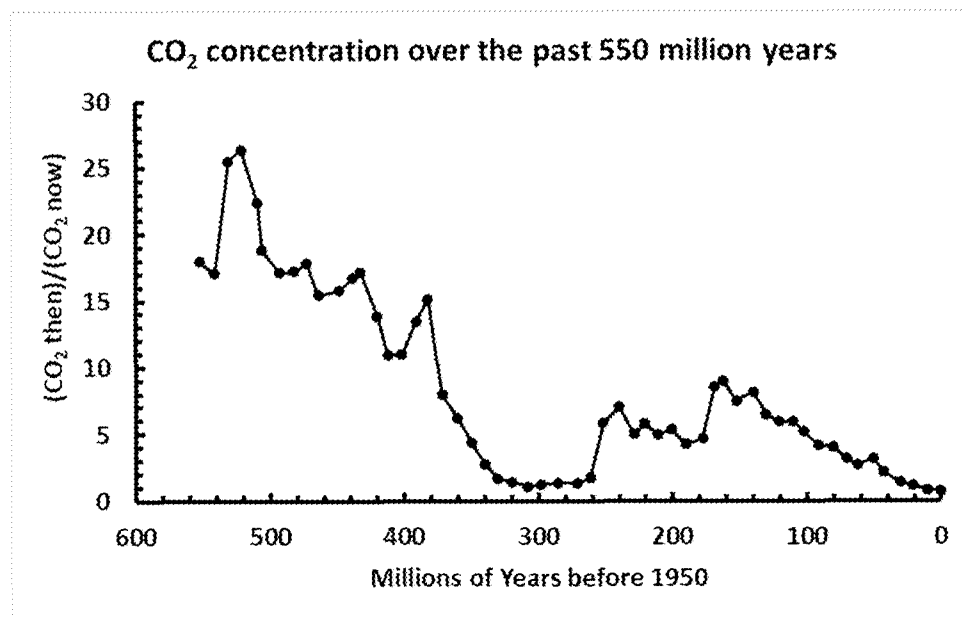


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels.
Source: Berner (2006)

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024).

Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

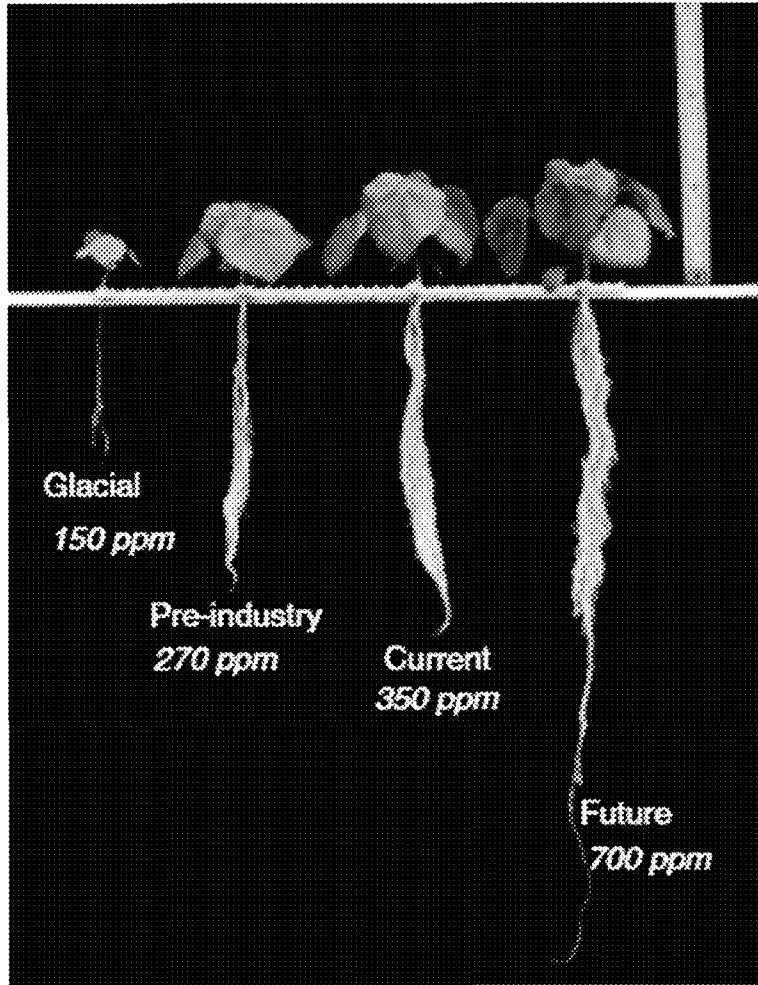


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed

by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

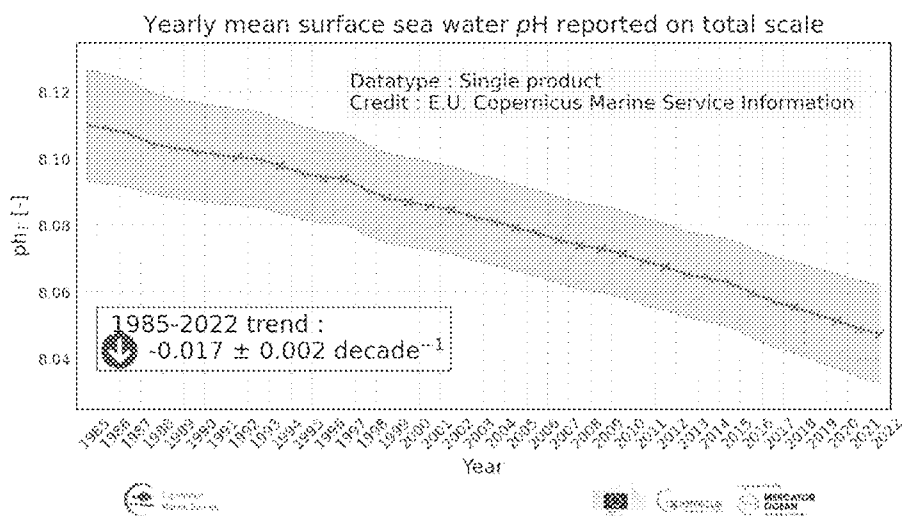


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

2.2.3 Publication bias

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.
Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

References

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>
- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Berner, R.A. (2006) GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
- Chen, Xin et al. (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791 <https://www.sciencedirect.com/science/article/pii/S2351989423004262>

- Cheng, L., Zhang, L., Wang, YP. *et al.* Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* **8**, 110 (2017). <https://doi.org/10.1038/s41467-017-00114-5>
- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 18 April 2016 DOI: 10.1038/NCLIMATE2995.
- Gerhart, Laci and Joy Ward (2010) Plant responses to low [CO₂] of the past. *New Phytologist* 188:674—695. <https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>
- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* **26**: 2390–2402.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, **764**, 142797.
- Judd, Emily et al. (2024) A 485-million-year history of Earth's surface temperature. *Science* **385** Issue 6715 <https://doi.org/10.1126/science.adk3705>
- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, **15**(10), e0241081.
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, **129**, 105–112.
- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, **112**, 125961.
- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* **1**:14–27
- Verhage, F. Y. (2017, November). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. Retrieved October 2024, from esalq: http://www.esalq.usp.br/departamentos/leb/eventos/Thesis_Report_-_Fabian_Verhage.pdf
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* **7**:432–436 May 2017 <https://www.nature.com/articles/nclimate3299>
- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* **5** June 2024 <https://www.nature.com/articles/s43247-024-01463-y>
- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* **6** Aug 2016 <https://www.nature.com/articles/nclimate3004>
- Australian Institute of Marine Science (2022). Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef. [https://www.aims.gov.au/sites/default/files/2022-08/AIMS LTMP Report on%20GBR coral status 2021 2022_040822F3.pdf](https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf)
- Beeden, R., Maynard, J., Puotinen, M., Marshall, P., Dryden, J., Goldberg, J., and Williams, G. (2015). Impacts and Recovery from Severe Tropical Cyclone Yasi on the Great Barrier Reef. *PLOS ONE*. **10**. e0121272. <https://doi.org/10.1371/journal.pone.0121272>
- Browman, H. (2016). Applying organized scepticism to ocean acidification research. *iCES Journal of Marine Science: Journal du Conseil*. **73**. 529.1–536. <https://doi.org/10.1093/icesjms/fsw010>
- Clements JC, Sundin J, Clark TD, Jutfelt F (2022) Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. *PLoS Biol* **20**(2): e3001511. <https://doi.org/10.1371/journal.pbio.3001511>
- De'ath, G., Lough, J., and Fabricius, K. (2009). Declining Coral Calcification on the Great Barrier Reef. *Science* (New York, N.Y.). **323**. 116–9. <https://doi.org/10.1126/science.1165283>

- Gattuso, J. P. and Hansson, L. (2011). Ocean acidification: background and history Ocean Acidification ed J P Gattuso and L Hansson (Oxford: Oxford University Press).
- Krissansen-Totton, J., Arney, G., and Catling, D. (2018). Constraining the climate and ocean pH of the early Earth with a geological carbon cycle model. *Proceedings of the National Academy of Sciences*. 115. 201721296. <https://doi.org/10.1073/pnas.1721296115>
- Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO₂ storage and release in the deep Southern Ocean on millennial to centennial timescales. *Nature*. 562. <https://doi.org/10.1038/s41586-018-0614-0>
- Revelle, R. R. and R. Fairbridge (1957). Carbonate and carbon dioxide, in *Treatise on Marine. Ecology and Paleoecology*, Vol. 1: J. W. Hedgpeth, ed.
- Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. *Marine Geology*. 346. 392–399. <https://doi.org/10.1016/j.margeo.2013.09.002>
- Woods Hole Oceanographic Institution (2023). Is the Great Barrier Reef Making a Comeback? <https://www.whoi.edu/oceanus/feature/is-the-great-barrier-reef-making-a-comeback/>
- Copernicus Marine Service (2025) Global Ocean acidification - mean sea water pH time series and trend from Multi-Observations Reprocessing. Online source https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description

2 Direct Impacts of CO₂ on the environment

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

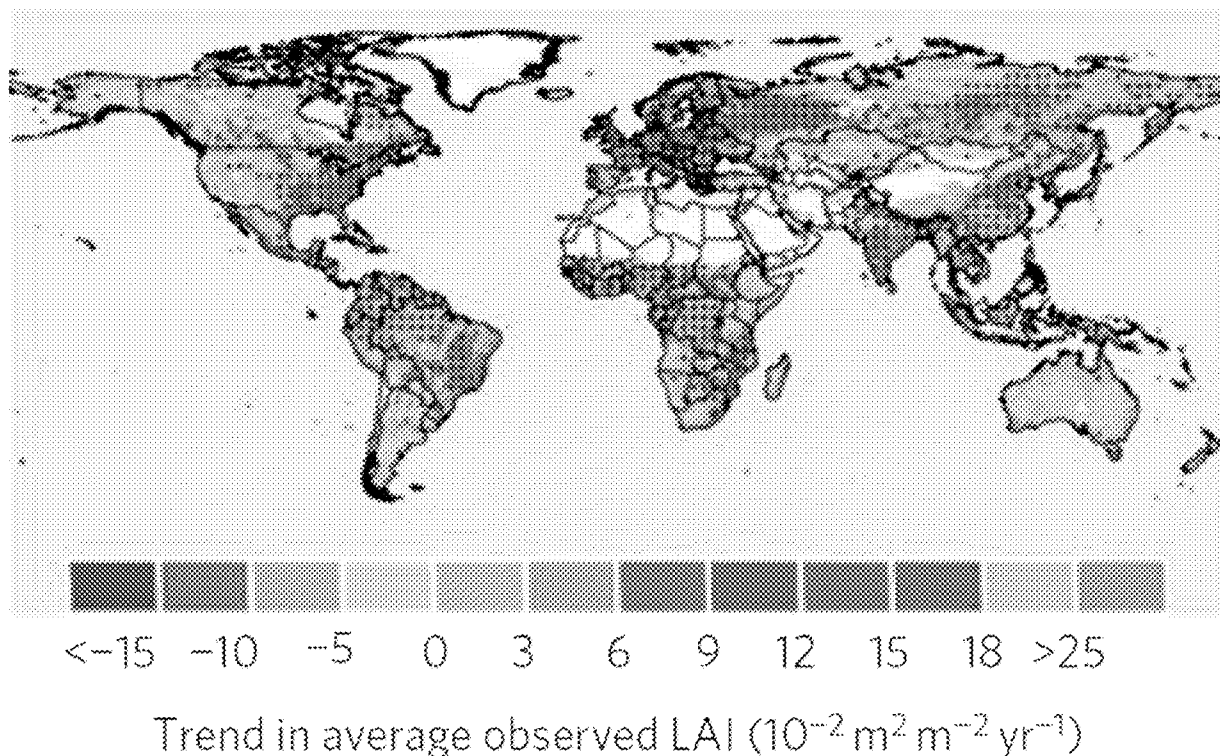


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

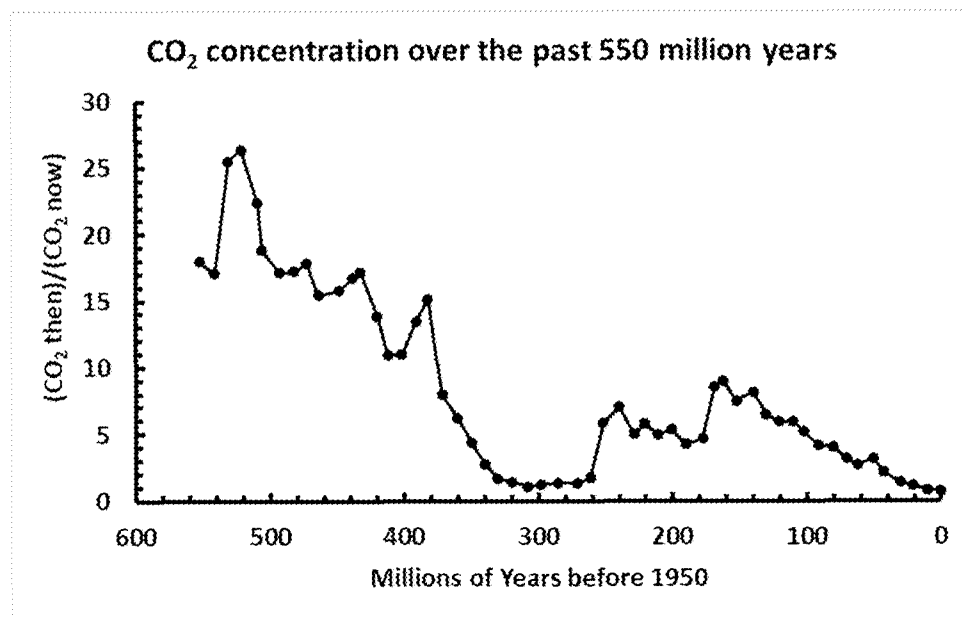


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels.
Source: Adapted from Berner (2006). Current CO₂ levels correspond to about 1.3 times the indicated value at 0.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024).

Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

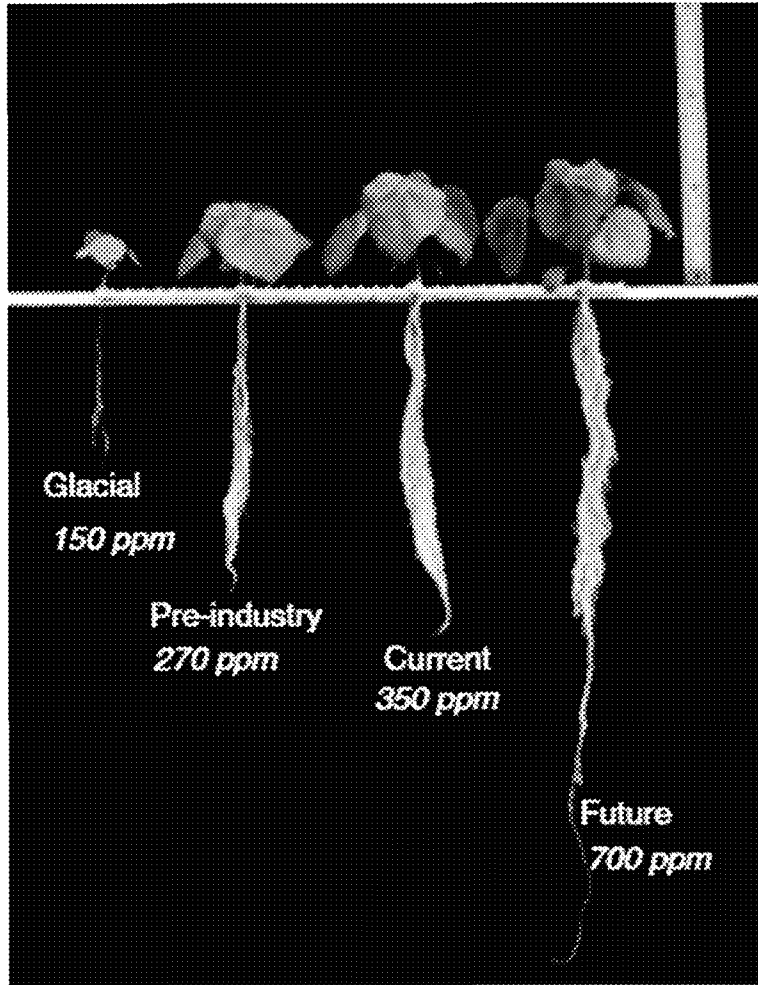


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed

by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

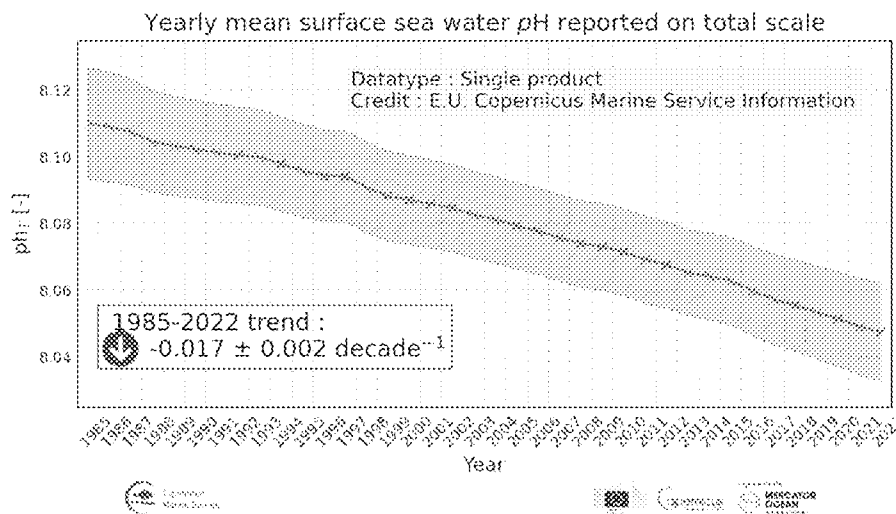


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods

Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

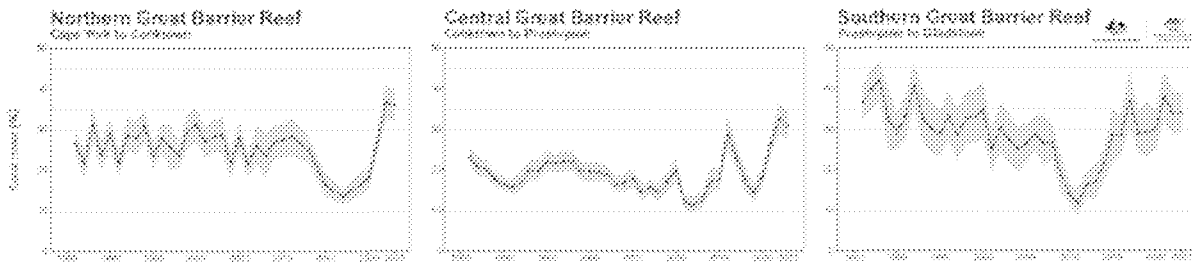


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

2.2.3 Publication bias

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An *ICES Journal of Marine Science* Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.

Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Changes to the Australian Great Barrier Reef are driven by many factors other than temperatures or alkalinity and coral cover has recently staged a major rebound. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

References

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>
- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Berner, R.A. (2006) GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
- Chen, Xin et al. (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791 <https://www.sciencedirect.com/science/article/pii/S2351989423004262>
- Cheng, L., Zhang, L., Wang, YP. et al. Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* 8, 110 (2017). <https://doi.org/10.1038/s41467-017-00114-5>
- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 18 April 2016 DOI: 10.1038/NCLIMATE2995.
- Gerhart, Laci and Joy Ward (2010) Plant responses to low [CO₂] of the past. *New Phytologist* 188:674—695. <https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>
- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* 26: 2390–2402.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, 764, 142797.
- Judd, Emily et al. (2024) A 485-million-year history of Earth's surface temperature. *Science* 385 Issue 6715 <https://doi.org/10.1126/science.adk3705>
- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, 15(10), e0241081.
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105-112.
- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, 112, 125961.
- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* 1:14-27
- Verhage, F. Y. (2017, November). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. Retrieved October 2024, from esalq: [http://www.esalq.usp.br/departamentos/leb/eventos/Thesis Report - Fabian Verhage.pdf](http://www.esalq.usp.br/departamentos/leb/eventos/Thesis%20Report%20-%20Fabian%20Verhage.pdf)
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* 7:432-436 May 2017 <https://www.nature.com/articles/nclimate3299>
- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 <https://www.nature.com/articles/s43247-024-01463-y>

- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* 6 Aug 2016
<https://www.nature.com/articles/nclimate3004>
- Australian Institute of Marine Science (2022). Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef.
[https://www.aims.gov.au/sites/default/files/2022-08/AIMS LTMP Report on%20GBR coral status 2021 2022 040822F3.pdf](https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf)
- Beeden, R., Maynard, J., Puotinen, M., Marshall, P., Dryden, J., Goldberg, J., and Williams, G. (2015). Impacts and Recovery from Severe Tropical Cyclone Yasi on the Great Barrier Reef. *PLOS ONE*. 10. e0121272. <https://doi.org/10.1371/journal.pone.0121272>
- Browman, H. (2016). Applying organized scepticism to ocean acidification research. *iCES Journal of Marine Science: Journal du Conseil*. 73. 529.1-536. <https://doi.org/10.1093/icesjms/fsw010>
- Clements JC, Sundin J, Clark TD, Jutfelt F (2022) Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. *PLoS Biol* 20(2): e3001511. <https://doi.org/10.1371/journal.pbio.3001511>
- De'ath, G., Lough, J., and Fabricius, K. (2009). Declining Coral Calcification on the Great Barrier Reef. *Science* (New York, N.Y.). 323. 116-9. <https://doi.org/10.1126/science.1165283>
- Gattuso, J. P. and Hansson, L. (2011). Ocean acidification: background and history *Ocean Acidification* ed J P Gattuso and L Hansson (Oxford: Oxford University Press).
- Krissansen-Totton, J., Arney, G., and Catling, D. (2018). Constraining the climate and ocean pH of the early Earth with a geological carbon cycle model. *Proceedings of the National Academy of Sciences*. 115. 201721296. <https://doi.org/10.1073/pnas.1721296115>
- Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO2 storage and release in the deep Southern Ocean on millennial to centennial timescales. *Nature*. 562. <https://doi.org/10.1038/s41586-018-0614-0>
- Revelle, R. R. and R. Fairbridge (1957). Carbonate and carbon dioxide, in *Treatise on Marine. Ecology and Paleoecology*, Vol. 1: J. W. Hedgpeth, ed.
- Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. *Marine Geology*. 346. 392–399. <https://doi.org/10.1016/j.margeo.2013.09.002>
- Woods Hole Oceanographic Institution (2023). Is the Great Barrier Reef Making a Comeback? <https://www.whoi.edu/oceanus/feature/is-the-great-barrier-reef-making-a-comeback/>
- Copernicus Marine Service (2025) Global Ocean acidification - mean sea water pH time series and trend from Multi-Observations Reprocessing. Online source [https://data.marine.copernicus.eu/product/GLOBAL OMI HEALTH carbon ph area averaged/description](https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description)
- Australia Institute of Marine Science (2023) AIMS' Annual Summary Report of Coral Reef Condition 2022/23 for the Great Barrier Reef. [https://www.aims.gov.au/sites/default/files/2023-08/QuickLook AIMS LTMP Report GBR coral status 22 23.pdf](https://www.aims.gov.au/sites/default/files/2023-08/QuickLook_AIMS_LTMP_Report_GBR_coral_status_22_23.pdf)

3 Human influences on the climate

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to space. Averaged over the Earth's surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. ~~Human (and some natural)~~ Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

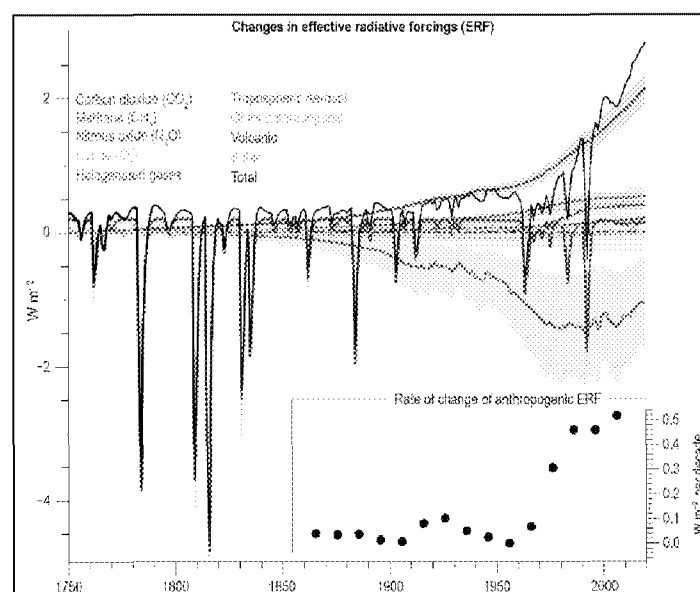


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

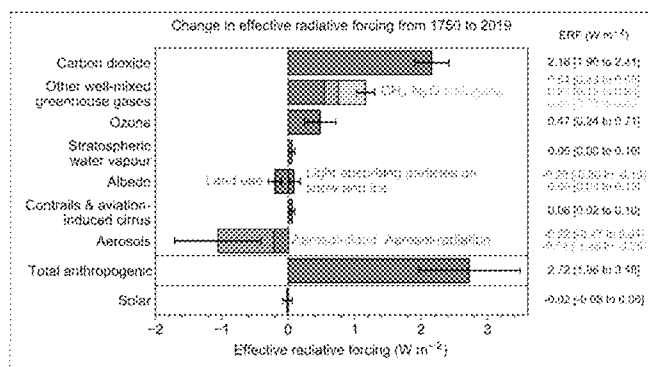


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called

the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how that gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

3.1.2 Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration above 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

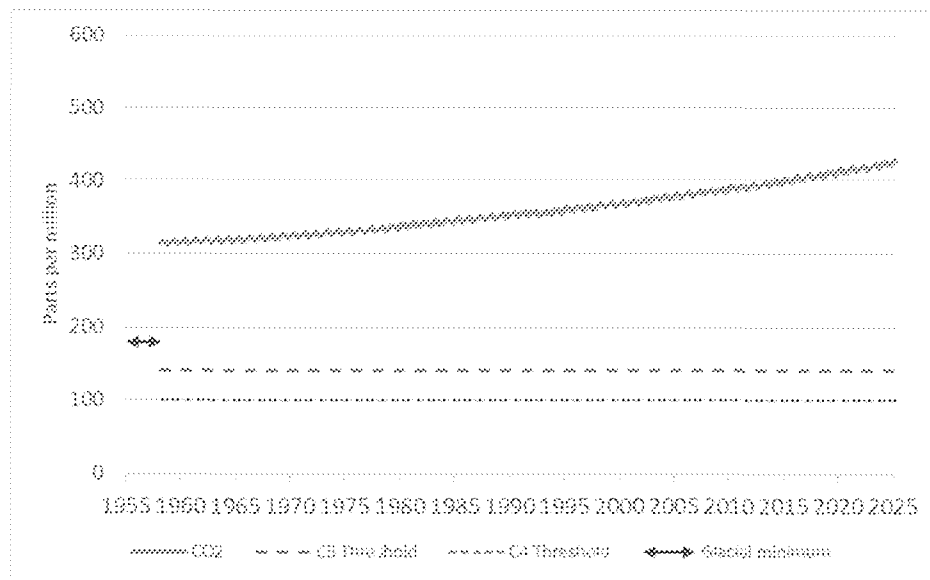


Fig. 3.1.3 CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow).

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts, they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SRES scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SRES scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles (p. 16) linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking below SSP2-5.

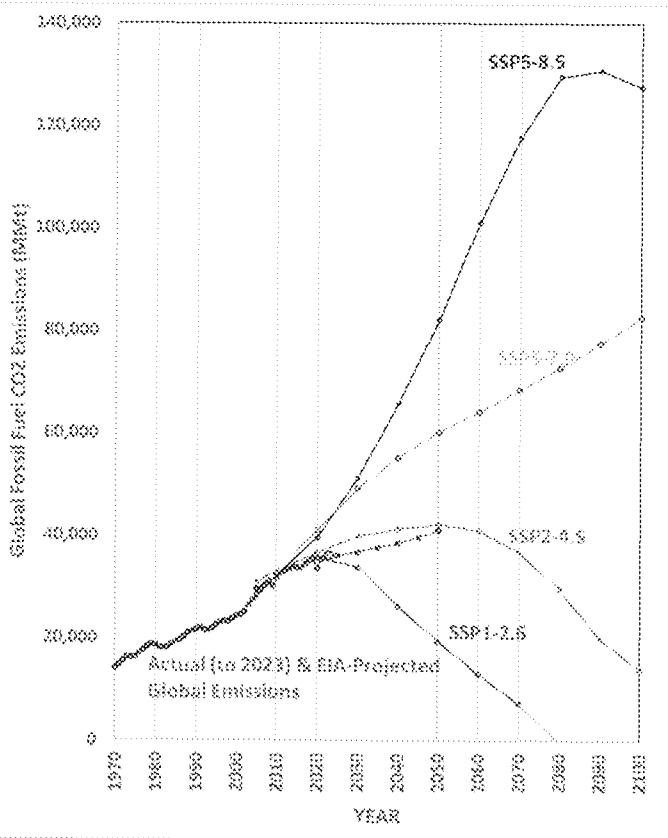


Figure 3.2.1. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1.

CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 2.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small - when emissions are reduced the local pollution

concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since carbon cycle is vast and slow. A change in local emissions today will have only a very small global effect, and even that only with a long delay. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently, it will take decades or centuries for U.S. CO₂ emission reductions to have a meaningful impact on the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up being too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions have minimal local effects, and only with a long delay. The practice of referring to unilateral US reductions as "combatting climate change" or "taking action on climate" reflects a profound misunderstanding of the scale of the issue. The scale problem is compounded by recognizing that U.S. motor vehicles account only for about 4 percent of global CO₂ emissions so that even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

Summary

- The global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.
- The IPCC has downplayed the role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it might have been important, and the modern record is uncertain due to an interruption in satellite coverage.
- IPCC emission scenarios have tended to exceed observed trends.

- The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading.
- Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.
- The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small, much delayed effects.

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129, <https://doi.org/10.1029/2024JD041296>

3 Human influences on the climate

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to warming. The modern record is uncertain in part due to an interruption in satellite coverage following the 1986 Space Shuttle Challenger disaster.

Climate projections are based on IPCC emission scenarios which have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading. Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.

The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small, much delayed effects.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

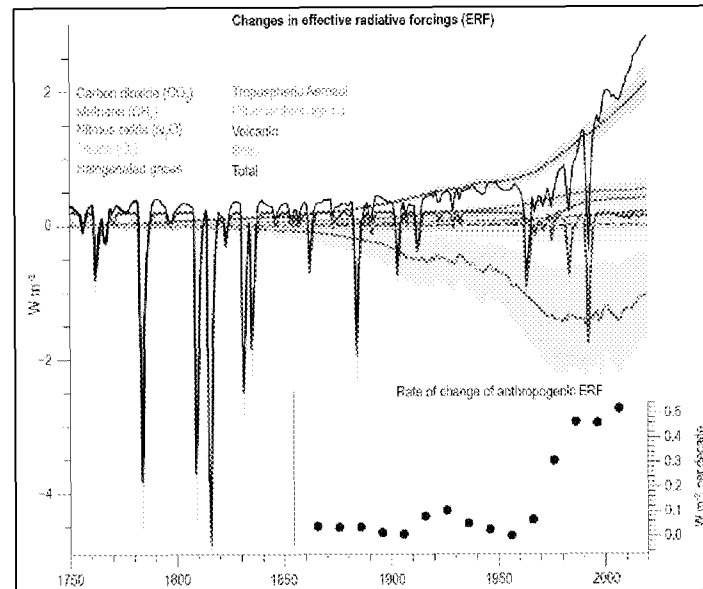


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

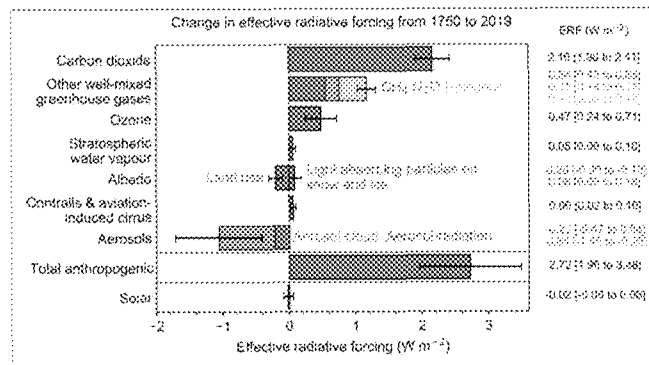


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy systems like motor vehicles. It exerts a warming influence by

decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how that gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

3.1.2 Urban heat islands and land use change

3.1.3 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration above 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

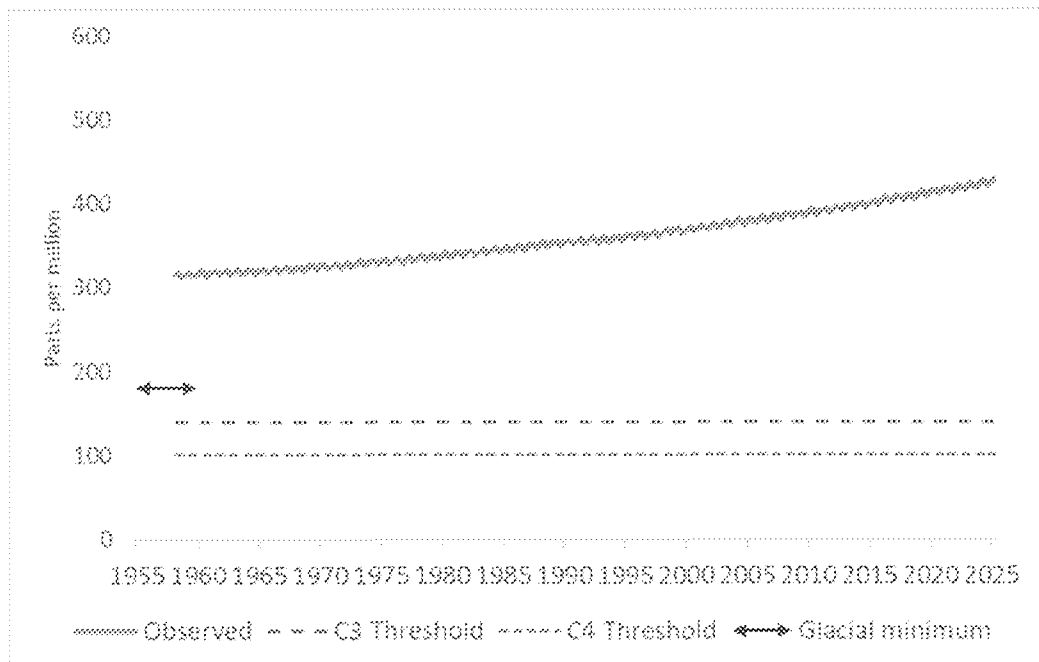


Fig. 3.1.3 CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold (green): Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold (grey): Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum (purple arrow): Minimum level during recent glaciations. CO₂ data source: <https://gml.noaa.gov/ccgg/trends/index.html>

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts, they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SRES scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SRES scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

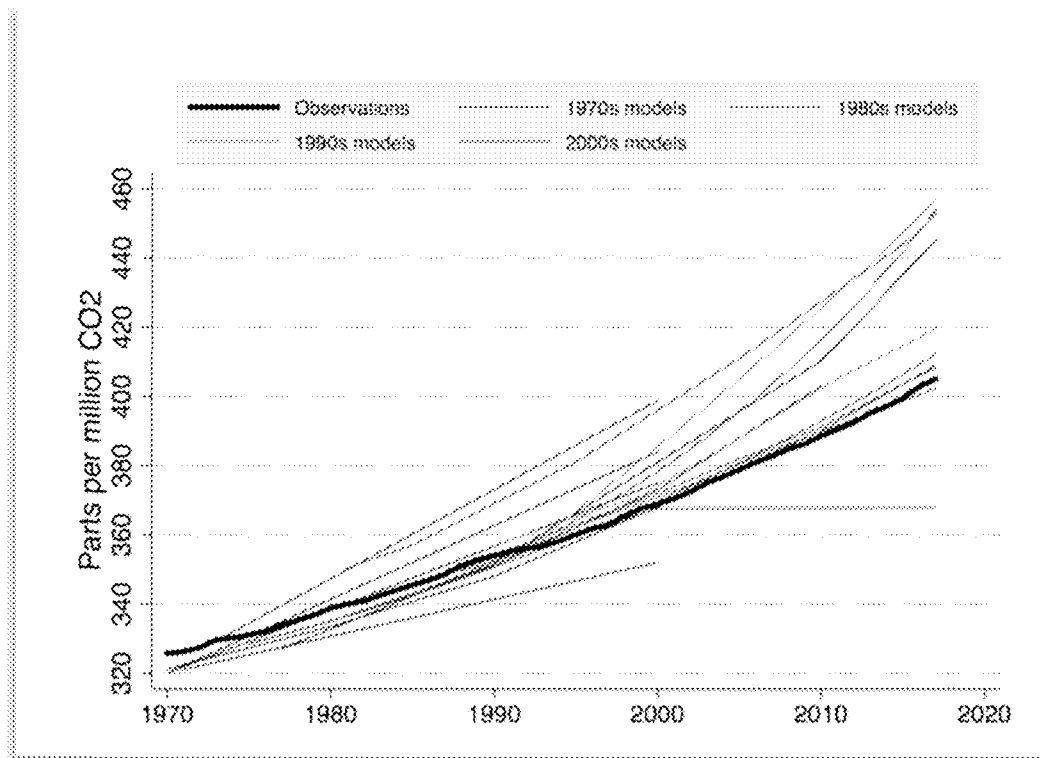


Figure 3.2.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather et al. (2019) Figure S4.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.2.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

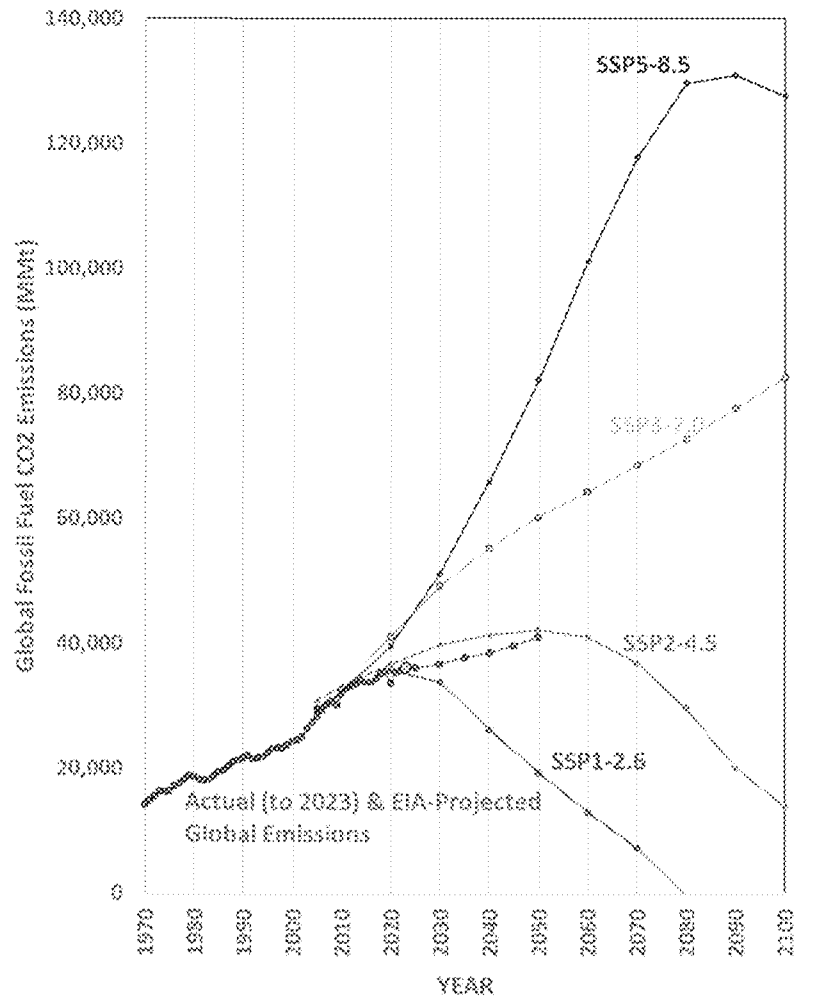


Figure 3.2.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 2.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Summary

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129, <https://doi.org/10.1029/2024JD041296>

4 Climate Sensitivity to CO₂ Forcing

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and so also the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney et al. 1979) proposed that the most likely ECS was $3.0 \pm 1.5^{\circ}\text{C}$. The IPCC repeatedly reaffirmed the range with only minor variations until its most recent AR6. AR5 termed $1.5 - 4.5^{\circ}\text{C}$ as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C .

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to $2.5-4.0^{\circ}\text{C}$ and deemed the *very likely* range to be $2.0 - 5.0^{\circ}\text{C}$. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0°C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based methods of computing climate sensitivity to GHGs

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 5.1). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by GCMs, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

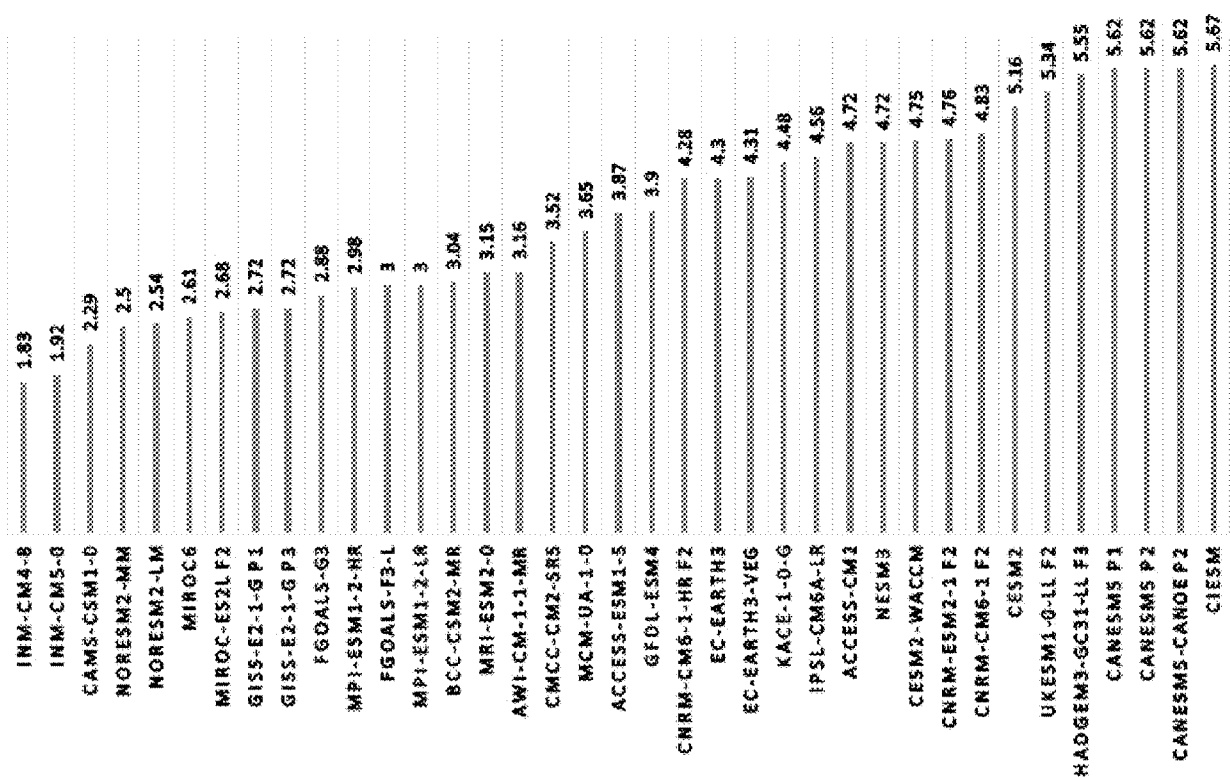


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

4.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects

need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”
Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentration where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is

no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

4.5 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS below the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

4.6 Summary

In the past 5 years, there is a growing realization that climate models (GCMs) are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to poorly resolved processes related to clouds and water vapor. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems* 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

1. Lan, X., Tans, P. and K.W. Thoning: Trends in globally-averaged CO₂ determined from NOAA Global Monitoring Laboratory measurements. Version Monday, 14-Apr-2025 09:08:57 MDT

<https://doi.org/10.15138/9N0H-ZH07>.

2. Zeke Hausfather, "Explainer: How Scientists Estimate Climate Sensitivity," *Carbon Brief*, July 22, 2020, <https://www.carbonbrief.org/explainer-how-scientists-estimate-climate-sensitivity>.
3. Jule Charney et al., "Carbon Dioxide and Climate: A Scientific Assessment," 1979, <https://doi.org/10.17226/12181>.
4. Rajendra K. Pachauri and Leo Meyer, *Climate Change 2014: Synthesis Report* (Geneva, CH: Intergovernmental panel on climate change, 2015).
5. "In-Depth Q&A: The IPCC's Sixth Assessment Report on Climate Science," Carbon Brief, August 9, 2021, <https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-report-on-climate-science>.
6. Nicola Scafetta, "Testing the CMIP6 GCM Simulations versus Surface Temperature Records from 1980–1990 to 2011–2021: High ECS Is Not Supported," *Climate* 9, no. 11 (2021): 161, <https://doi.org/10.3390/cli9110161>.
7. Brian J. Soden and Isaac M. Held, "An Assessment of Climate Feedbacks in Coupled Ocean–Atmosphere Models," *Journal of Climate* 19, no. 14 (July 15, 2006): 3354–3360, <https://doi.org/10.1175/jcli3799.1>.
8. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence," *Reviews of Geophysics* 58, no. 4 (July 22, 2020), <https://doi.org/10.1029/2019rg000678>.
9. Judith A. Curry and Peter J. Webster, "Thermodynamic Feedbacks in the Climate System," in *Thermodynamics of Atmospheres and Oceans* (New York, NY: Academic Press, 1999), 351–385.
10. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
11. D. Chen et al., "Framing, Context, and Methods."
12. Mark D. Zelinka et al., "Causes of Higher Climate Sensitivity in CMIP6 Models," *Geophysical Research Letters* 47, no. 1 (2020): e2019GL085782, <https://doi.org/10.1029/2019GL085782>.
13. Thorsten Mauritsen and Johann Jungclaus, "Tuning the MPI-ESM1.2 Global Climate Model to Improve the Match With Instrumental Record Warming by Lowering Its Climate Sensitivity," *Journal of Advances in Modeling Earth Systems* 12, no. 7 (2020): e2019MS002037, <https://doi.org/10.1029/2019MS002037>.
14. Alexander Otto et al., "Energy Budget Constraints on Climate Response," *Nature Geoscience* 6, no. 6 (May 19, 2013): 415–416, <https://doi.org/10.1038/ngeo1836>.
15. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?" *Atmospheric Chemistry and Physics* 24, no. 5 (2024): 2679–2686, <https://doi.org/10.5194/acp-24-2679-2024>.
16. "Why Low-End 'Climate Sensitivity' Can Now Be Ruled Out," Carbon Brief, July 22, 2020, <https://www.carbonbrief.org/guest-post-why-low-end-climate-sensitivity-can-now-be-ruled-out>.
17. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity."
18. D. Chen et al., "Framing, Context, and Methods."
19. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence," *Climate Dynamics* 61, no. 9–10 (2023): 3155–3163, <https://doi.org/10.1007/s00382-022-06398-8>.
20. Ibid.
21. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?"

22. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)," *EGUsphere* [preprint], 2025, <https://doi.org/10.5194/egusphere-2025-1179>.
 23. P. Forster et al., (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V. et al. (eds.)], Cambridge University Press, 2021.
 24. Richard Seager et al., "Strengthening Tropical Pacific Zonal Sea Surface Temperature Gradient Consistent with Rising Greenhouse Gases," *Nature Climate Change* 9, no. 7 (2019): 517–522, <https://doi.org/10.1038/s41558-019-0505-x>.
 25. Sangyeop Lee et al., "Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint," *Climate Dynamics* 62, no. 1–2 (2024): 229–246, <https://doi.org/10.1007/s00382-023-06741-7>.
 26. D. Chen et al., "Framing, Context, and Methods."
 27. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
 28. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
 29. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
 30. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)."
- Nierenberg, William et al. (1983) *Changing Climate: Report of the Carbon Dioxide Assessment Committee*. Washington, National Academies Press 1983.

5 Models versus Observations in the Recent Past

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide the theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. In order to determine the value of climate models for this purpose, it is reasonable to ask how well they have reproduced climate variations over the recent past, say the last half-century.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

5.2 Surface warming

A straightforward test of climate model validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 6.1 is reproduced from Scaffeta (2023), a peer-reviewed 2023 study which groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

Columns correspond to model groups showing low-ECS to high-ECS. Rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

Examination of the leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

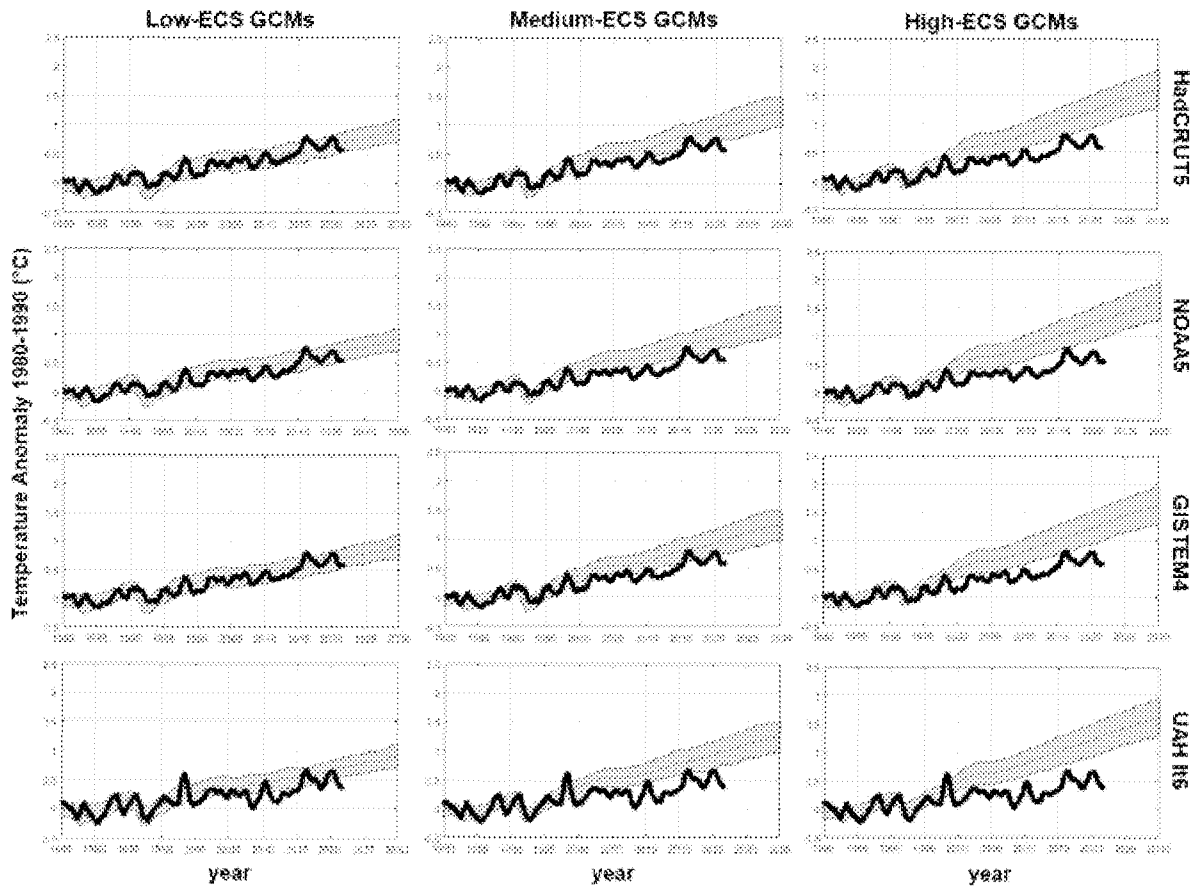


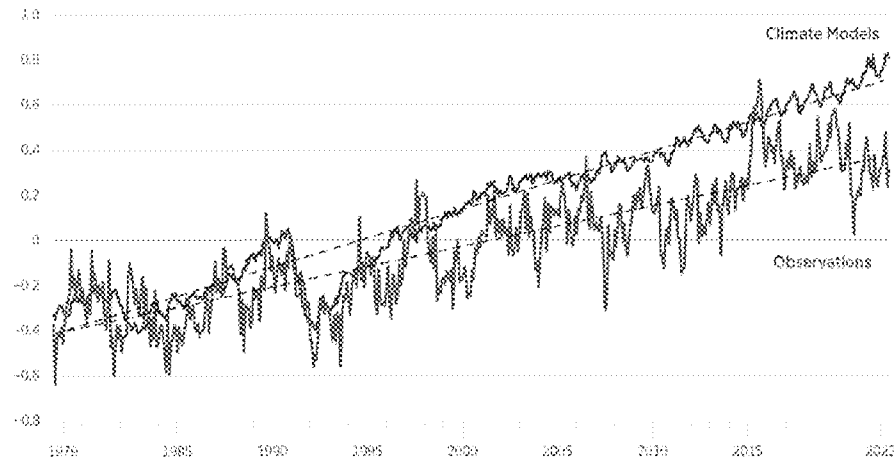
Figure 5.1: model-observational comparisons for Earth's surface warming. Source: Scafetta N. Climate Dynamics 2023 Fig.2. Rows: temperature data products as indicated. Columns: Low- to High-ECS models. Observations: black line. Model simulations: yellow band.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by focusing on average surface temperature data products versus the average climate model warming, summarized in Figure 6.2.

CHART 1

Global Average Surface-Air Temperature Variations, 1979~2022

DEPARTURE FROM 1951-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Authors' calculations based on data from five different observation-based datasets and 35 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and NOAA Climate Explorer, "Starting Point," <https://climate.noaa.gov/Start.asp> (accessed January 10, 2024).

Figure 5.2: Models versus observations at the surface. Source: Spencer (2024)

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the troposphere over the tropics. Since this region generates the bulk of atmospheric warming in a GCM it is important to get the trends right. The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time not better, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 5.3). Every single model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 5.4).

In most individual cases the bias is statistically significant and on average it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If a group of models were to appear that had a realistic representation of global tropospheric warming, it would likely have to have a lower ECS than even the low-ECS members of the CMIP6 ensemble

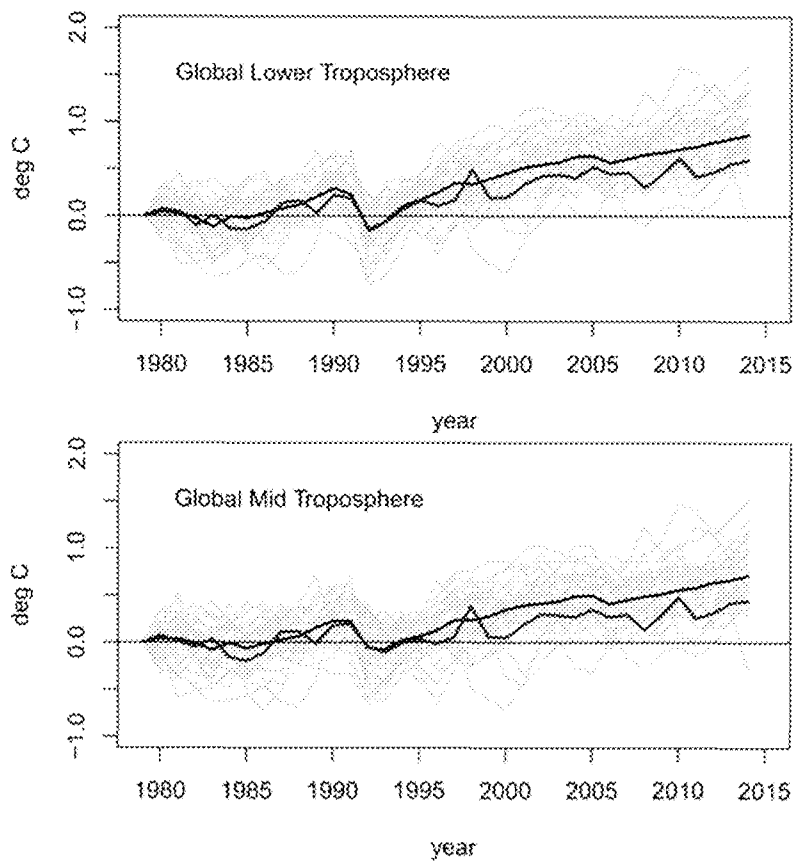


Figure 5.3: Models versus observations in the global troposphere. Source: McKittrick and Christy (2020). Gray lines: model runs. Black: average model run. Blue: average of satellite, radiosonde and reanalysis observations.

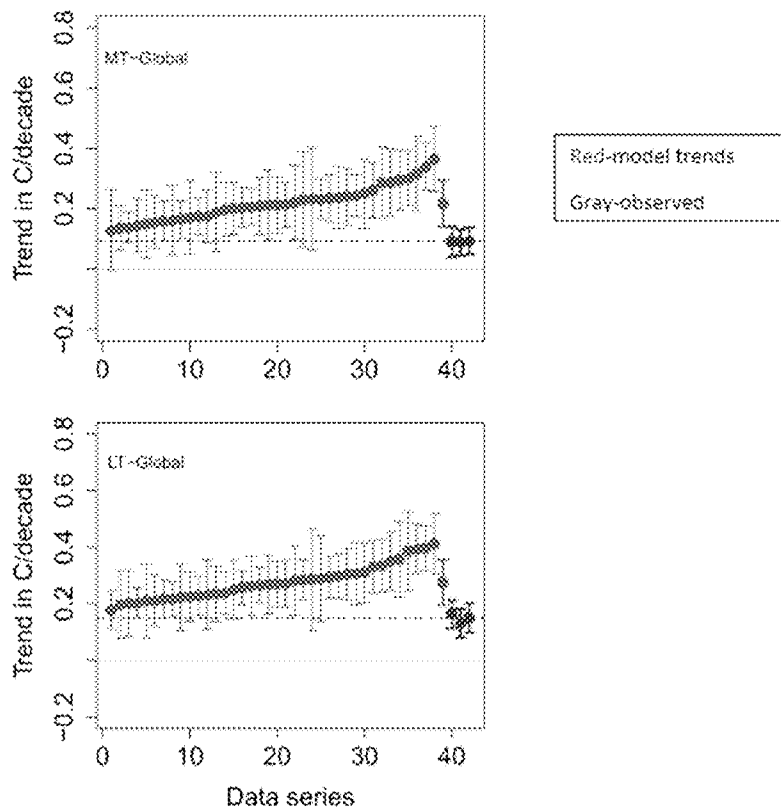
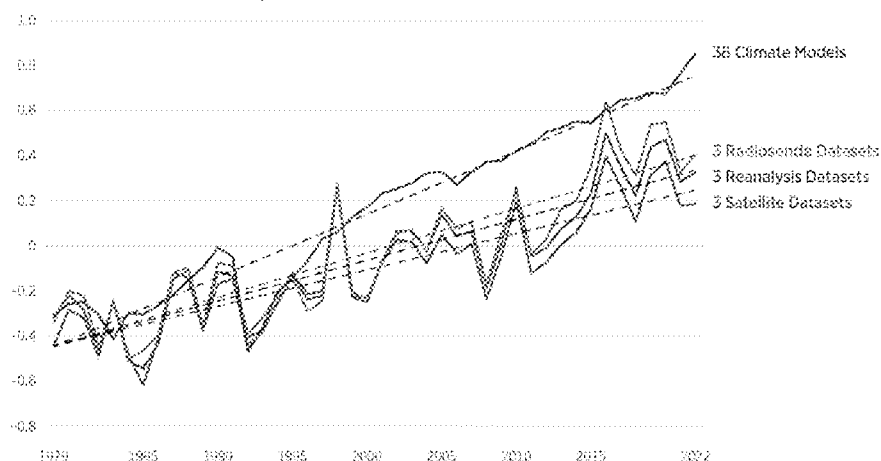


Figure 5.4: Modeled versus observed warming trends in the global troposphere. Adapted from McKittrick and Christy (2020). Red dots: model warming trend in $^{\circ}\text{C}/\text{decade}$ with 95% confidence interval bars. Gray dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars.

Spencer (2024) shows the mismatch is also present in the lower troposphere:

Global Lower Atmospheric Temperature Variations, 1979-2022

DEPARTURE FROM 1991-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES:

- Author's calculations based on data from Ross McKittrick and John Christy, "Persistent Warming Bias in CMIP6 Tropospheric Layers," *Earth and Space Science*, Vol. 7, No. 11 (Nov 14, 2020), <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020EF000128> (accessed January 10, 2023).
- Author's calculations based on data from American Meteorological Society, *State of the Climate in 2022*, <https://www.wamweather.gov/index.cfm/analysis/outlook/bulletin-of-the-american-meteorological-society-bulletin-of-the-climate/> (accessed January 9, 2023).

BG3809 heritage.org

Figure 5.5: Comparison of average trends in lower troposphere, 1979-2022. Source: Spencer (2024).

As mentioned the IPCC has long acknowledged the model-observational mismatch. The AR6 pp. 443-444 confirms model-observational mismatch in the troposphere the tropics (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5

and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

It is worth noting that despite the enormous accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias. In other contexts they declare *high confidence* in phenomena established with much less evidence.

5.4 Vertical profile mismatch and excess amplification

An important element of the model-observational discrepancy is the excess amplification with altitude found in climate models. A comparison was shown in the IPCC AR5 Chapter 10, although only in the online supplement. The diagram, reproduced below as Figure 5.6, compares temperature trends by altitude between models and observations, divided up into latitude bands.

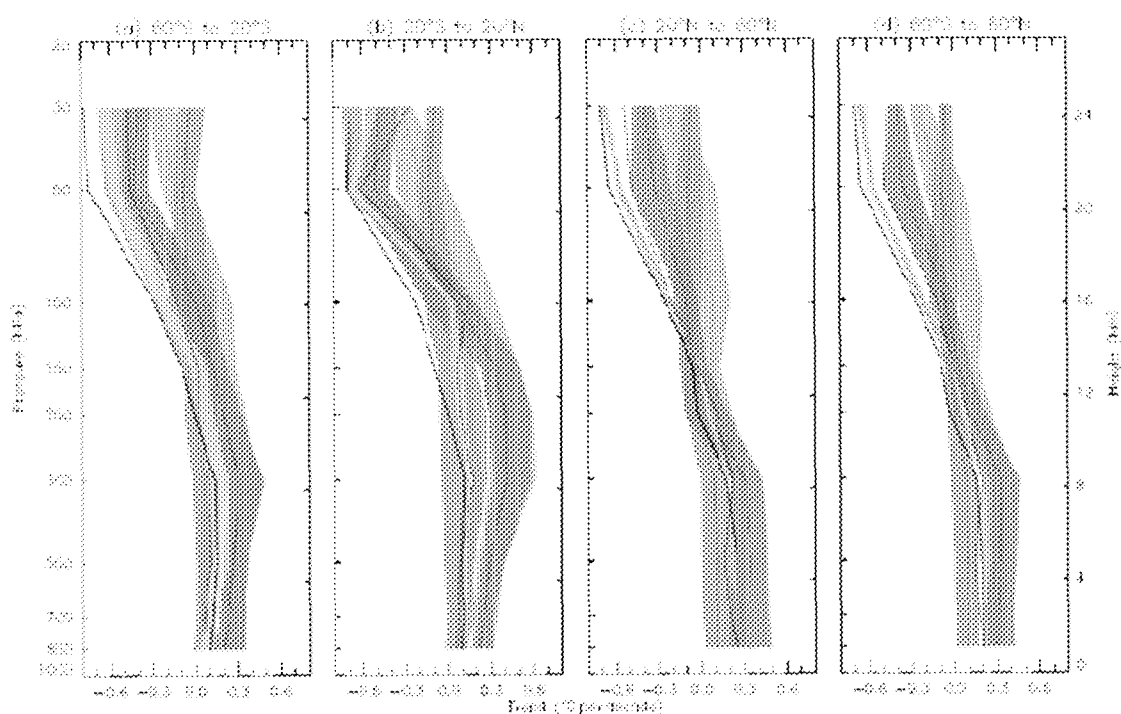


Figure 10.SM.1 | Observed and simulated mean temperature trends from 1979 to 2010 for CMIP5 simulations containing both anthropogenic and natural forcings (left), natural forcings only (blue) and greenhouse gas forcing only (green) where the 5th to 95th percentile ranges of the ensembles are shown. Three radiance observations are shown: black (left line: Hadley Centre Atmospheric Temperature data set 2 (HadAT2)), dark black (line: Radiance Observation Collection using Radiance (RADOC)) 1.5, dark gray (line: Radiance Observation Composite reinterpolation (RAC10-obs 1.5) ensemble and light gray (RAC10-1.5 ensemble (adapted from Li et al. (2018) but for the more recent period from 1979 to 2010).

10562-6

Figure 5.6: Vertical warming pattern by latitude band. Source: IPCC AR5 Figure 10.SM.1

The Figure is not referenced in the main report nor in any summary. What it shows, although it is not apparent at first glance, is that the 1979-2010 warming in the lower troposphere is so minimal it is consistent with models having no GHG forcing in them at all, and is inconsistent with the model runs that do have GHG forcing. Here is the main global band (60S to 60N) expanded with the observed trends highlighted in yellow:

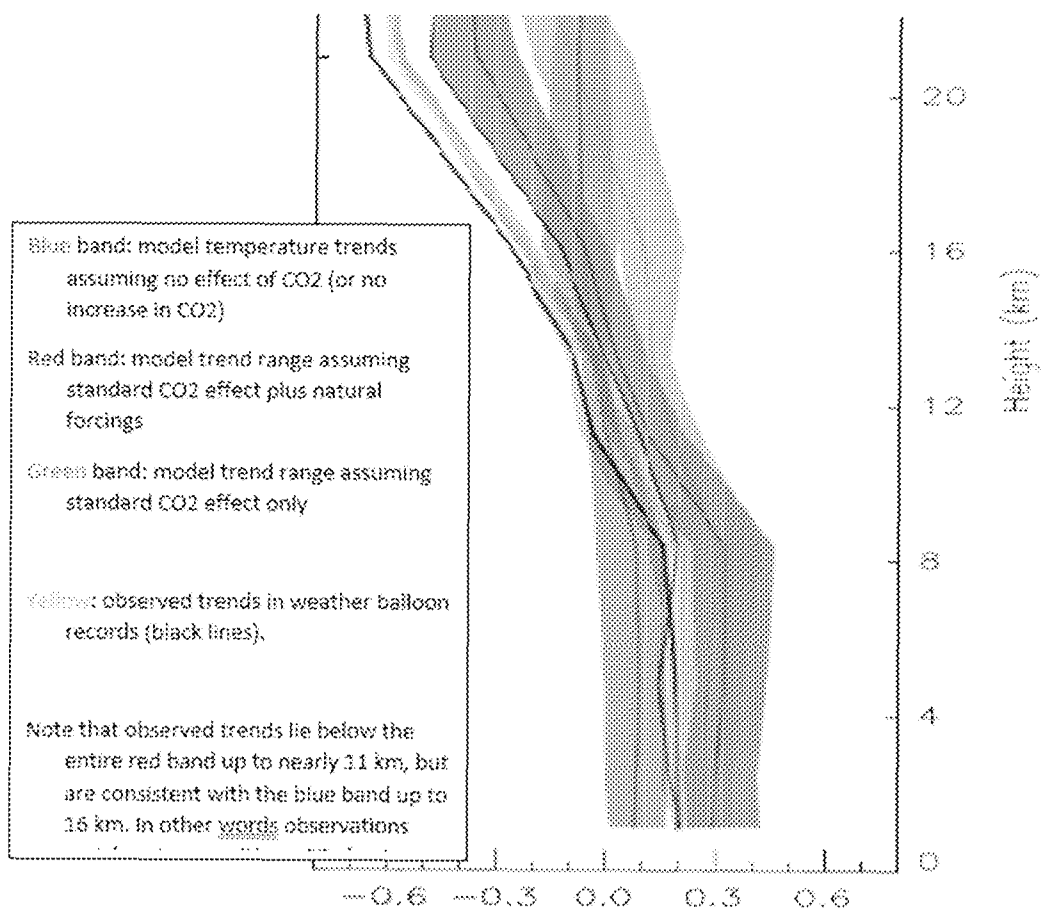


Figure 5.7: Adapted from IPCC AR5 Figure 10.SM.1

The next version of the Figure draws further detail out of the tropics band:

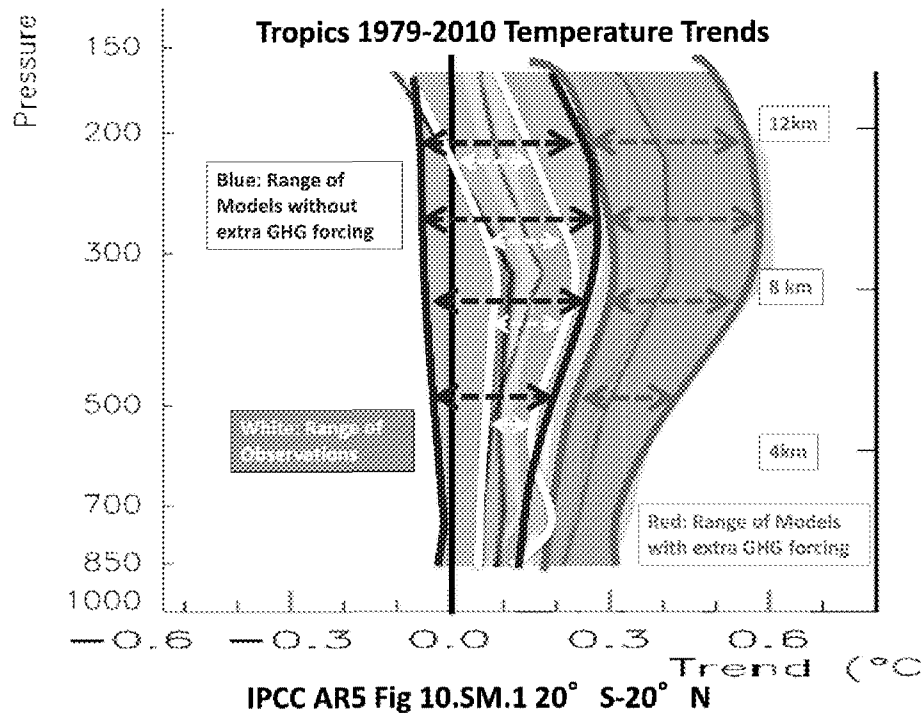


Figure 5.8: Adapted from IPCC AR5 Figure 10.SM.1.

In the tropics, where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.9. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.9 is the TTT layer average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

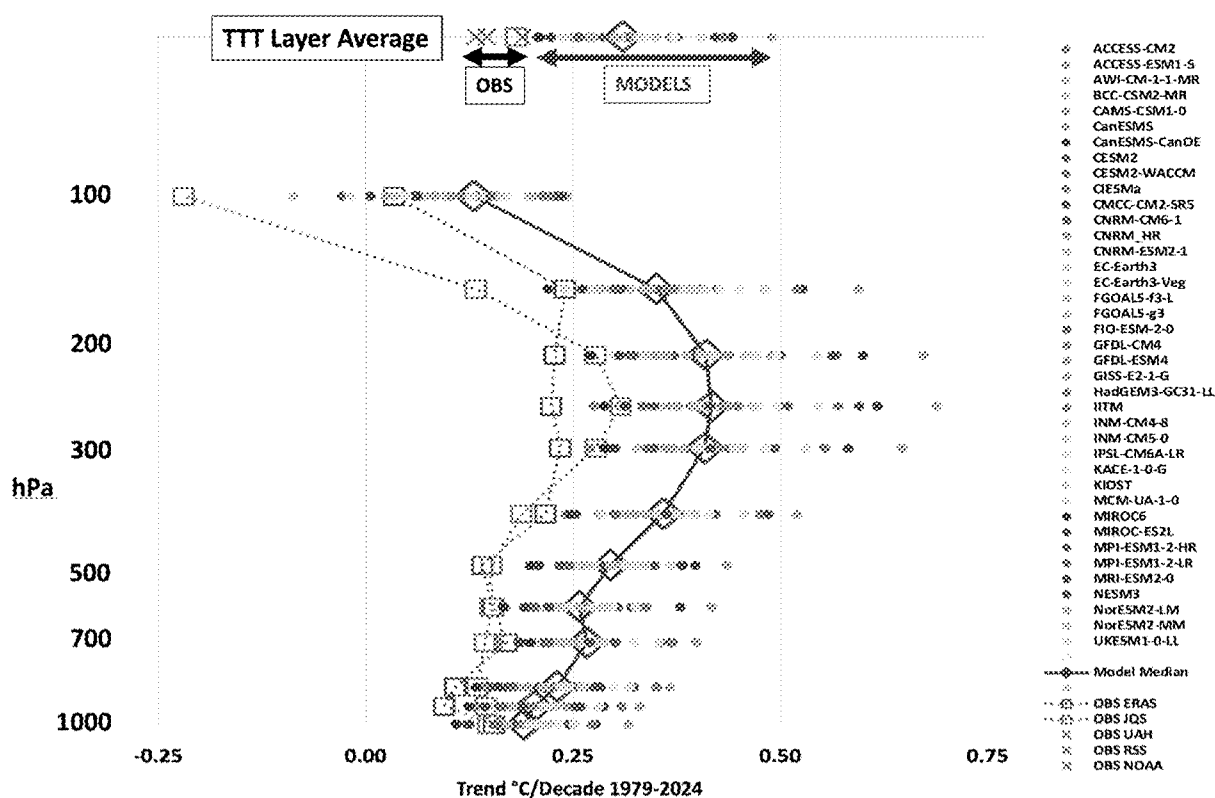


Figure 5.9: Modeled versus observed warming, tropical troposphere. Source: Christy and McNider (2017).

Some defenders of the models have argued that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), which was not discussed in the AR6, showed that models project greater amplification with altitude than is observed. That paper gave rise to an online debate over whether the amplification rates were being correctly calculated, and whether the discrepancy between models and observations was statistically significant. The topic involves very advanced statistical theory and was dealt with by two experts in time series analysis (Vogelsang and Nawaz 2016) who found that Klotzbach’s conclusions were valid, and that observed amplification is significantly smaller than the model-projected rates. The IPCC AR6 made no mention of this work either.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.”

5.6 Water vapour trends mismatch

Much of the warming in climate models derives not from GHG increases themselves but from water vapour feedbacks: extra warming induced by the projected accumulation of water vapour in the atmosphere after it warms due to CO₂. But new evidence (Simpson et al. 2024) shows that models have over-projected increases in humidity.

“Water vapor in the atmosphere is expected to rise with warming because a warmer atmosphere can hold more moisture. However, over the last four decades, near-surface water vapor has not increased over arid and semi-arid regions. This is contrary to all climate model simulations in which it rises at a rate close to theoretical expectations, even over dry regions. This may indicate a major model misrepresentation of hydroclimate-related processes; models increase water vapor to satisfy the increased atmospheric demand, while this has not happened in reality.”
(Simpson et al. 2024)

While the models and observations matched over the 1988 to 2006 interval they diverge after that, directly contradicting model projections.

5.7 Snow cover mismatch

According to the Rutgers University Snow Lab (undated) the Northern Hemisphere winter snow cover shows an increasing trend over time.

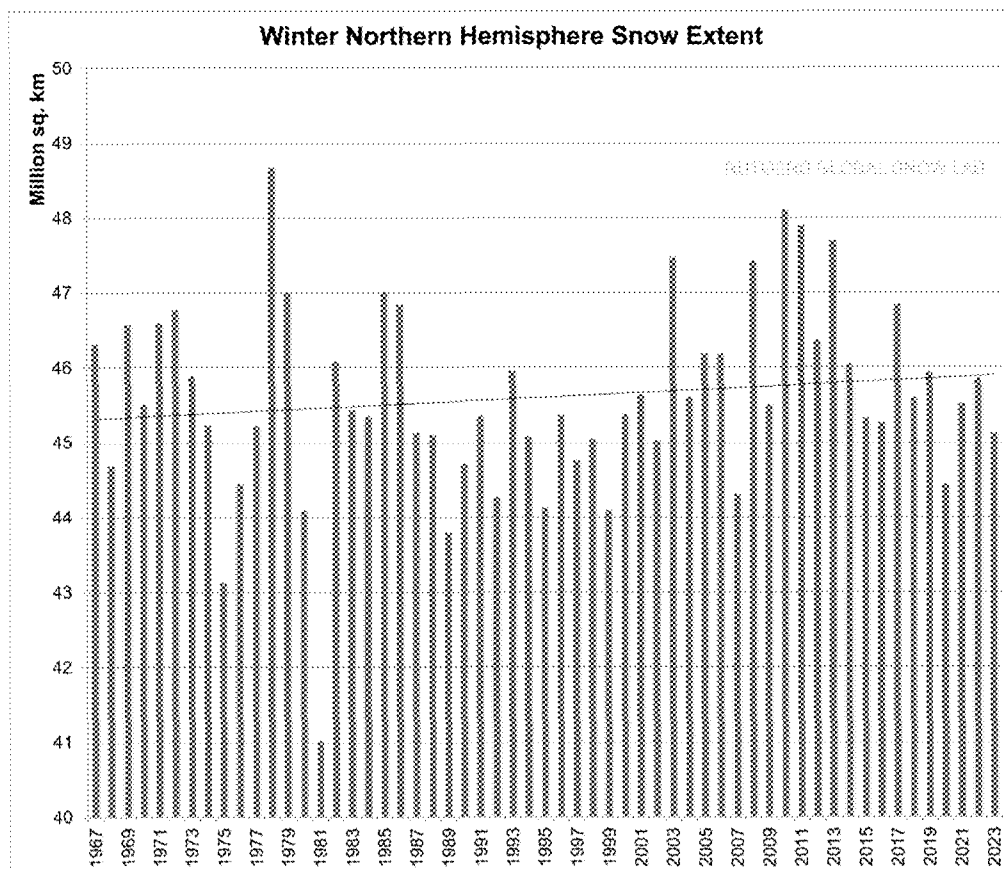


Figure 5.10: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (February 24, 2024)

Models project declining Northern Hemisphere snow cover due to climate warming. But observations do not support this, as explained by Connolly et al. (2019).

Observed changes in Northern Hemisphere snow cover from satellite records were compared to those predicted by all available Coupled Model Intercomparison Project Phase 5 (“CMIP5”) climate models over the duration of the satellite’s records, i.e., 1967–2018. A total of 196 climate model runs were analyzed (taken from 24 climate models). Separate analyses were conducted for the annual averages and for each of the seasons (winter, spring, summer, and autumn/fall). A longer record (1922–2018) for the spring season which combines ground-based measurements with satellite measurements was also compared to the model outputs. **The climate models were found to poorly explain the observed trends. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions.** Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant. Connolly et al. (2019), emphasis added.

5.8 US Corn Belt

One of the largest discrepancies between models and observations can be found when we test them in a region of particular importance to global food production: the U.S. Corn Belt. Fig. 6.11 shows the warming trends for summertime (June, July, August) for the U.S. 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) produced too much warming compared to observations (blue) during 1973 to 2022.

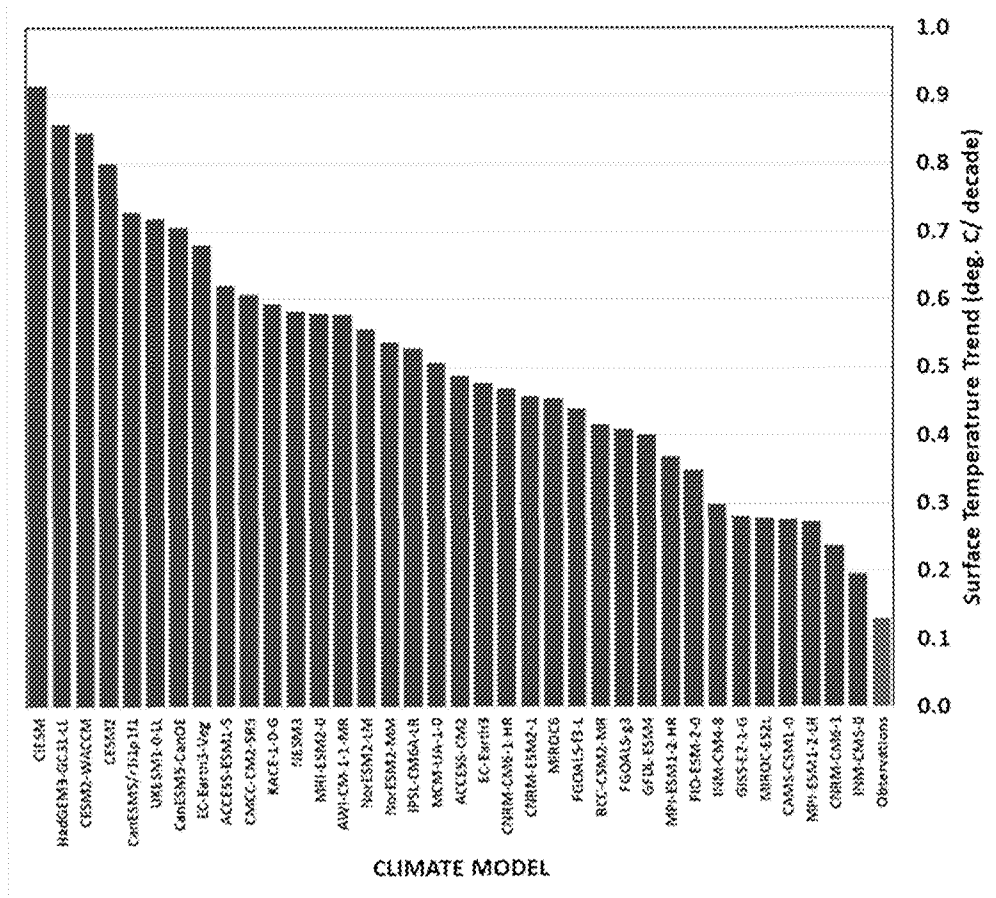


Figure 5.11: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, which is in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt.
- The IPCC has acknowledged some of these issues, buried the amplification problem and ignored others.

- The warm bias discussed here is consistent with independent evidence of model bias presented in Chapters 4 (measuring climate sensitivity) and 8 (optimal fingerprinting). Given the persistent warm bias in so many key aspects of climate model performance, users are justified in assuming that projections of future warming are also very likely to be biased too warm.

6 Extreme weather

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 6.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is not present in a given century-long record.

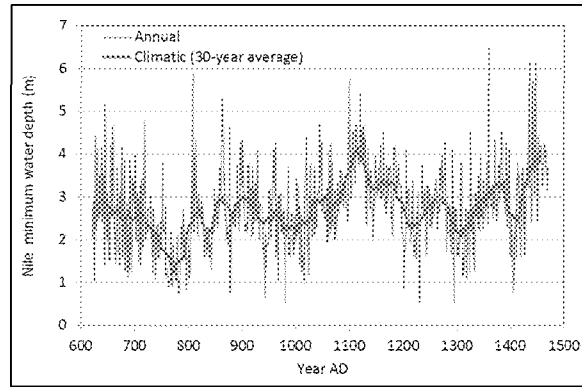


Figure 6.1.1: Nile River discharge [details, source]

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I.

NCA23: The US *Climate Science Special Report of the Fifth National Climate Assessment* (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis is added.

6.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 9 looks at causal attribution, with Section 9.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a

detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

6.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

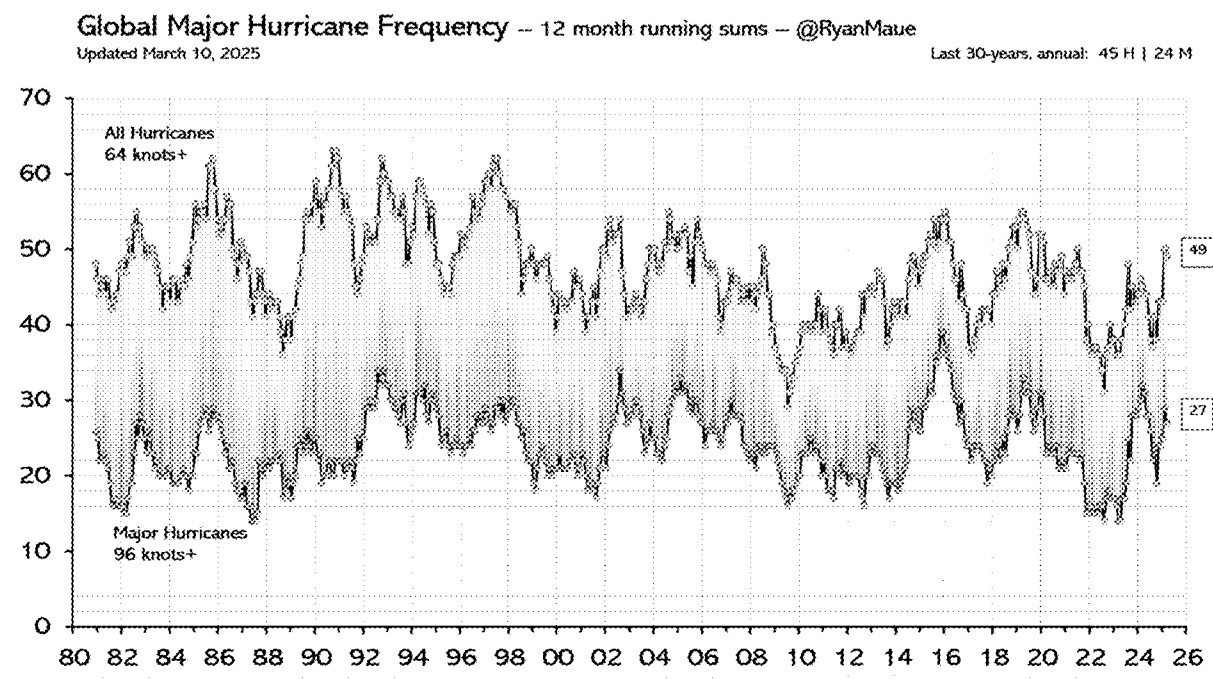


Figure 6.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35 percent of total global hurricanes whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 6.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

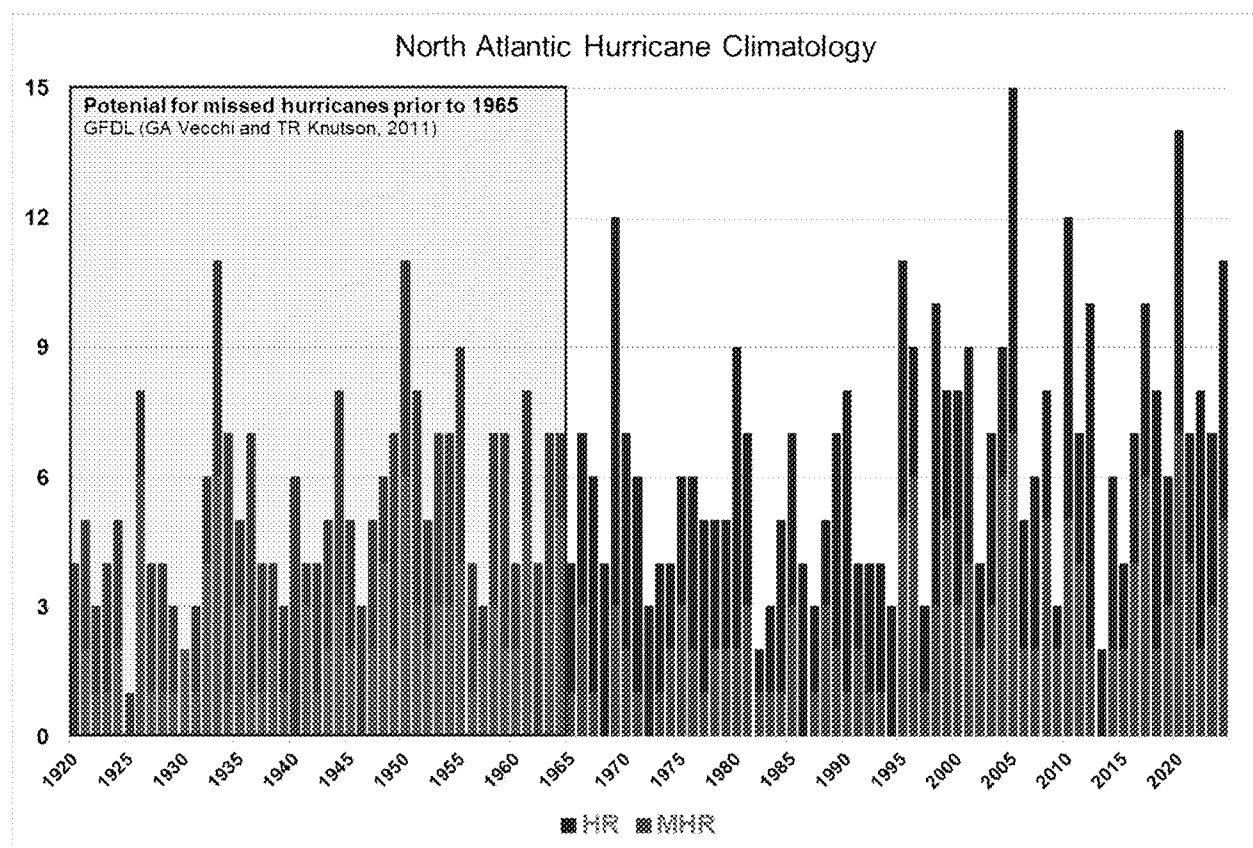


Figure 6.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 6.3.2 that Atlantic hurricanes show strong variations on decadal and multidecadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified

by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 6.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

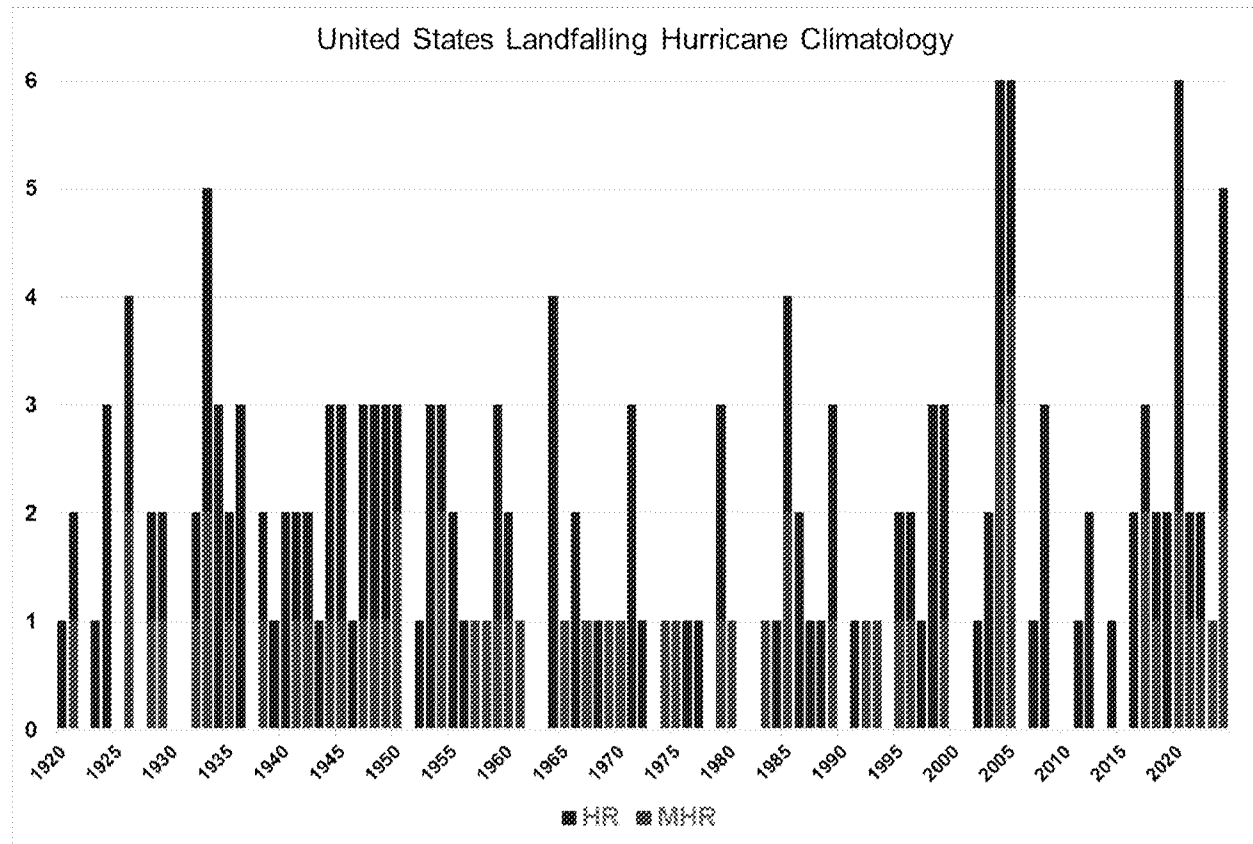


Figure 6.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 6.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 6.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 6.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

6.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: “Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s.**” (pp. 190-191)

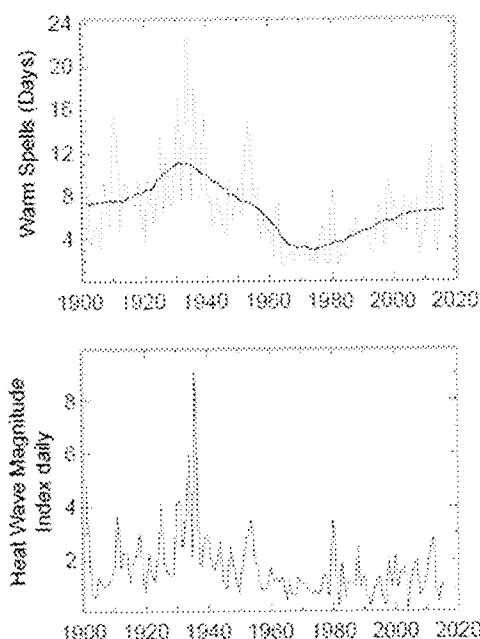


Figure 6.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

6.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

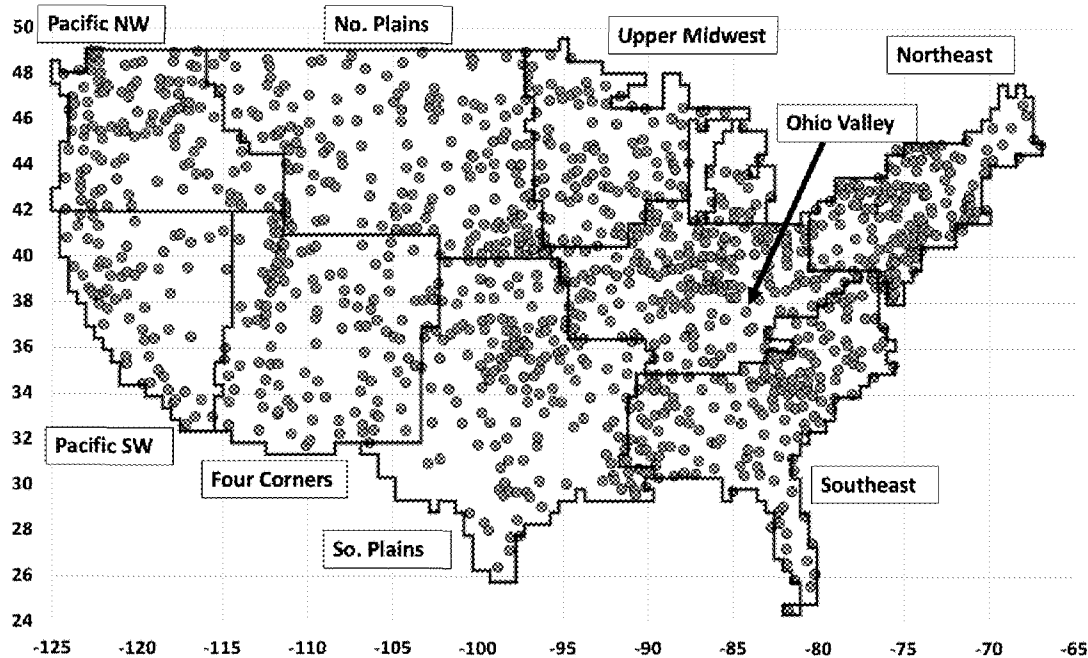


Figure 6.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 6.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

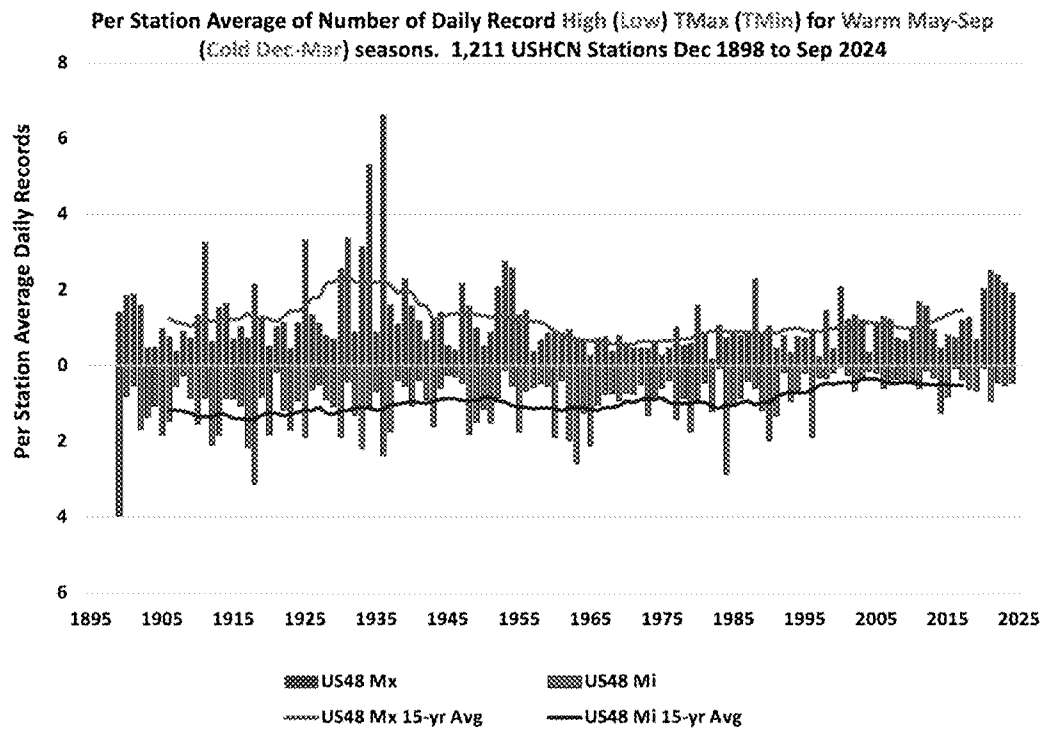


Figure 6.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

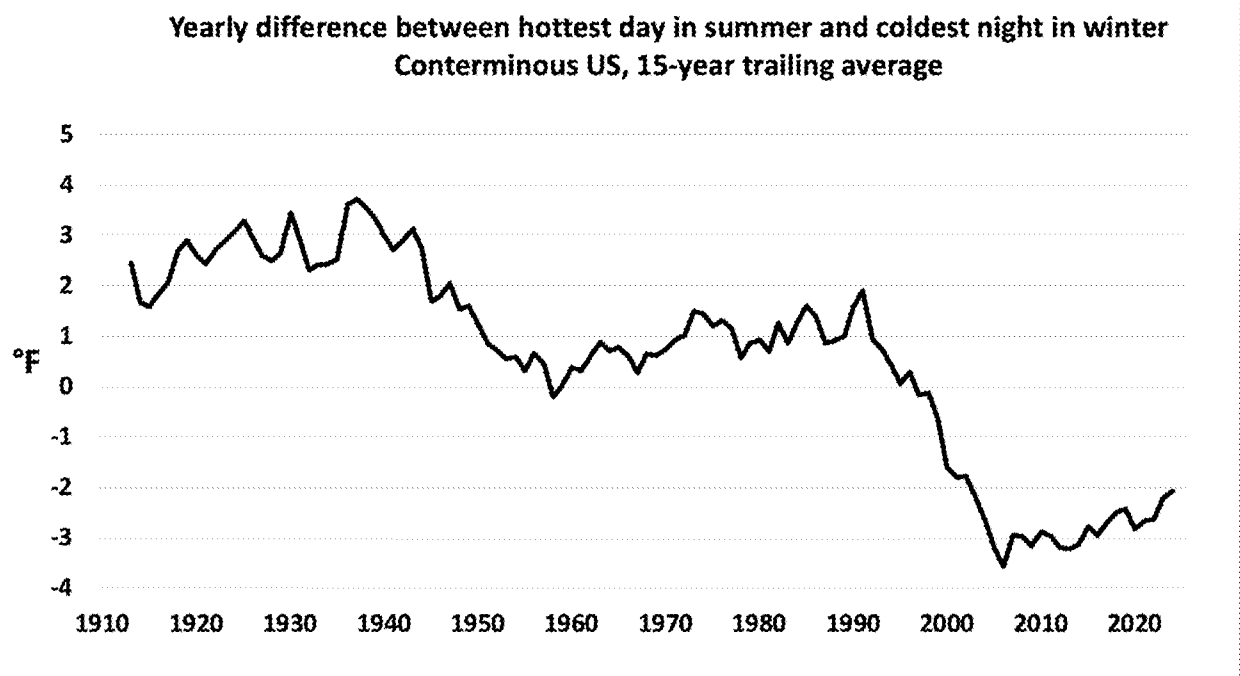


Figure 6.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

6.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

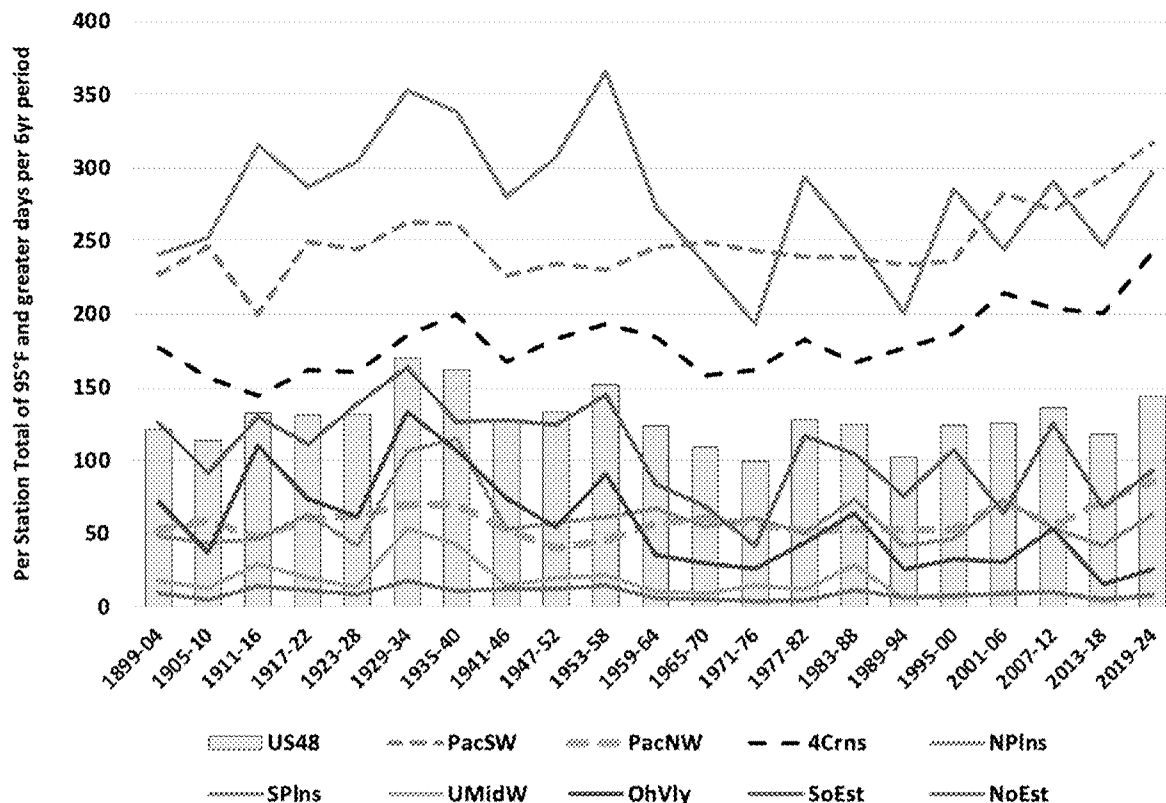


Figure 6.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced in the NCA23, an event we examine more closely in Section 8.4. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” WHERE IS THIS HEADING FROM – Perhaps NCA23? suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the figures above.

6.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

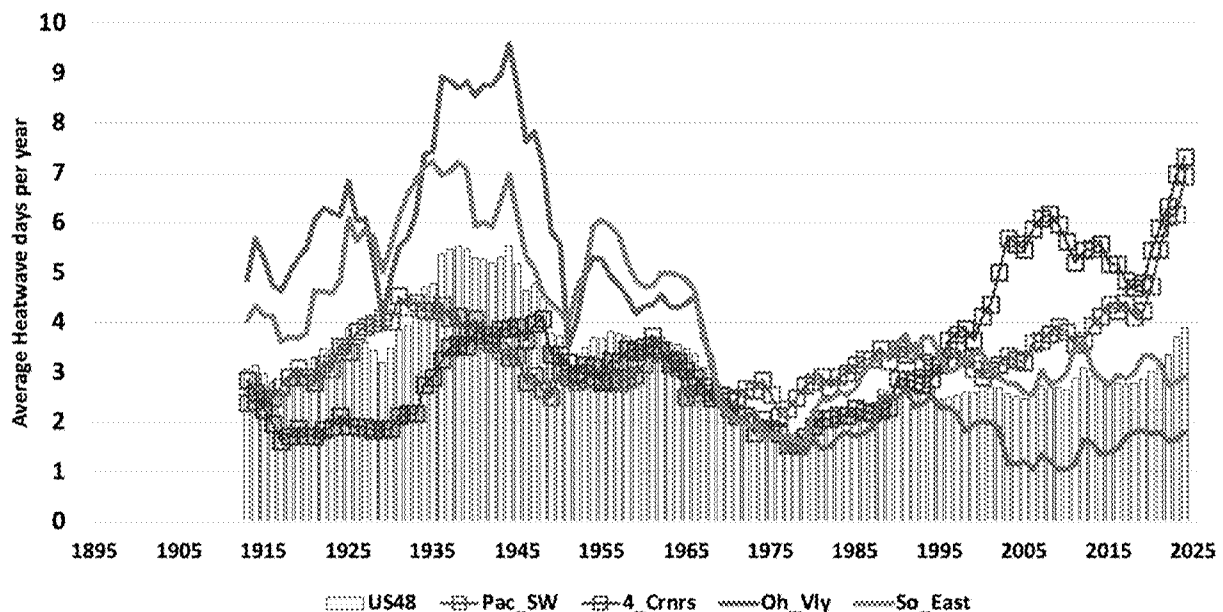


Figure 6.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 6.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

6.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

6.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

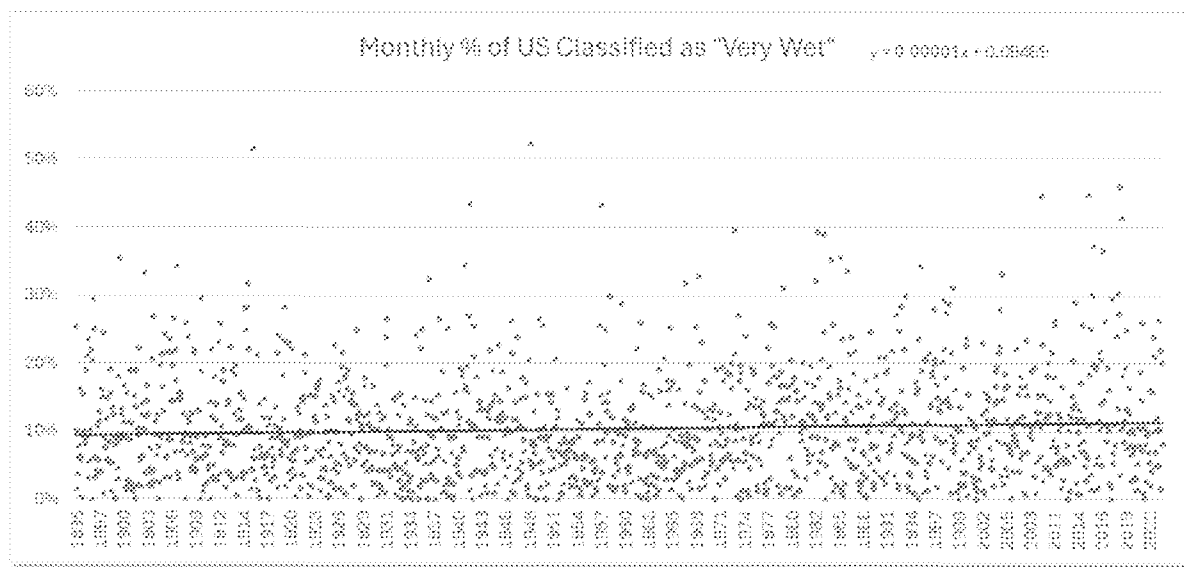


Figure 6.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 6.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 6.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, in a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 6.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While

erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

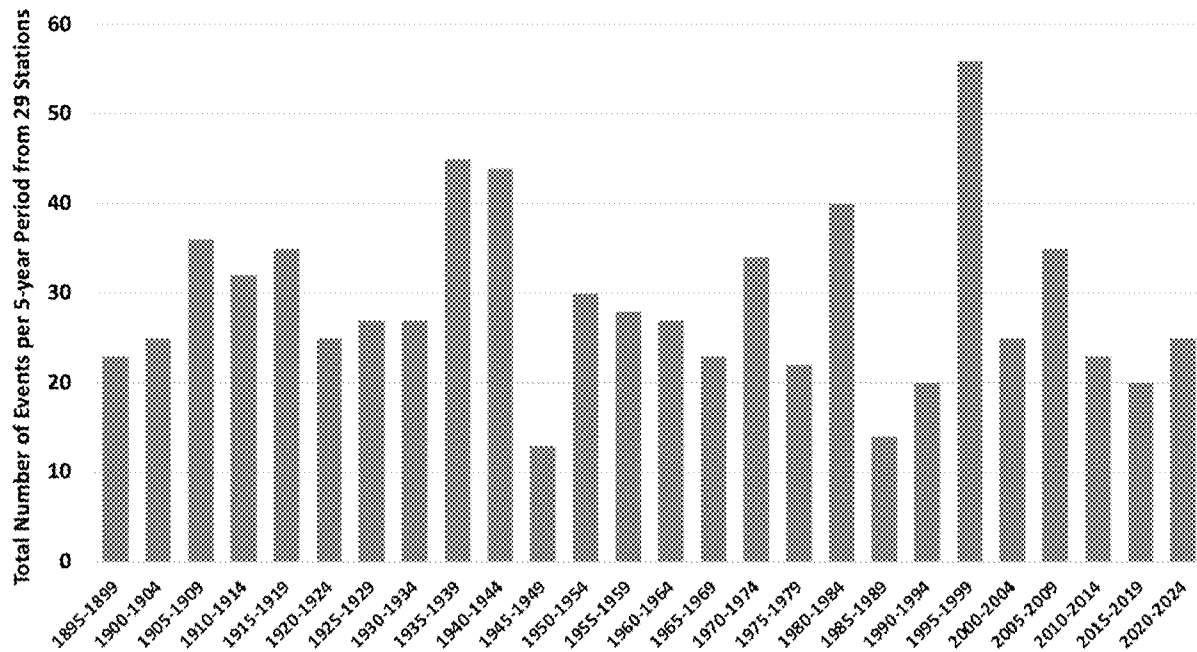


Figure 6.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

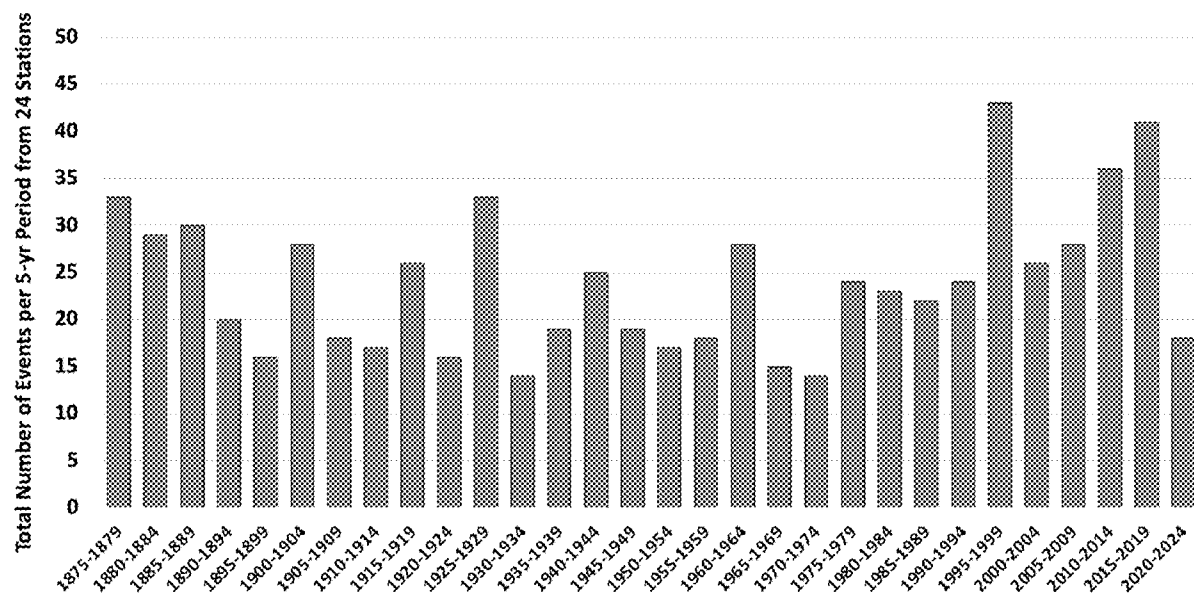


Figure 6.5.4. As in Fig. 6.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME; insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 6.5.5 shows the same calculation for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it shall be examined more closely.

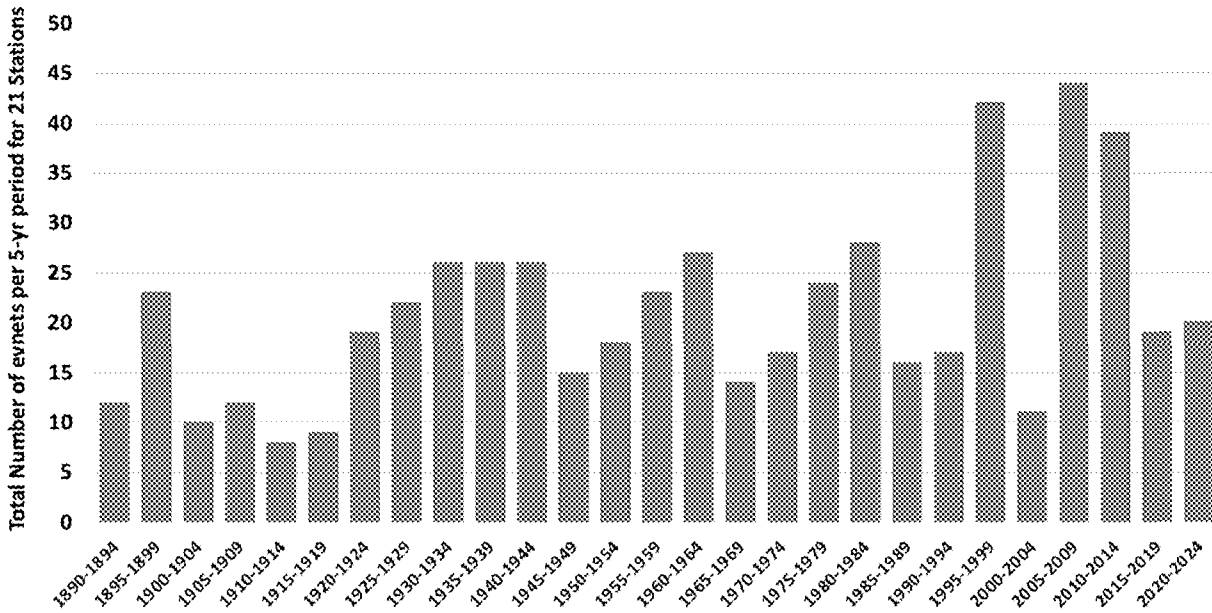


Figure 6.5.5. As in Fig. 7.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 21 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 6.5.5 that includes PA and NJ and reported differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes. They reported a dramatic increase (317%) in 24-hr events exceeding 6 inches. Using the information in Fig. 6.5.5 over the same years we find a 51% increase in the frequency of heavy events. However the frequency drops sharply after 2014, returning to the long-term average over the next decade. It was thus unfortunate that Howarth et al. sample ended in 2014.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.5.5 and 6.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, the pattern was not region-wide nor did the change persist after 2014.

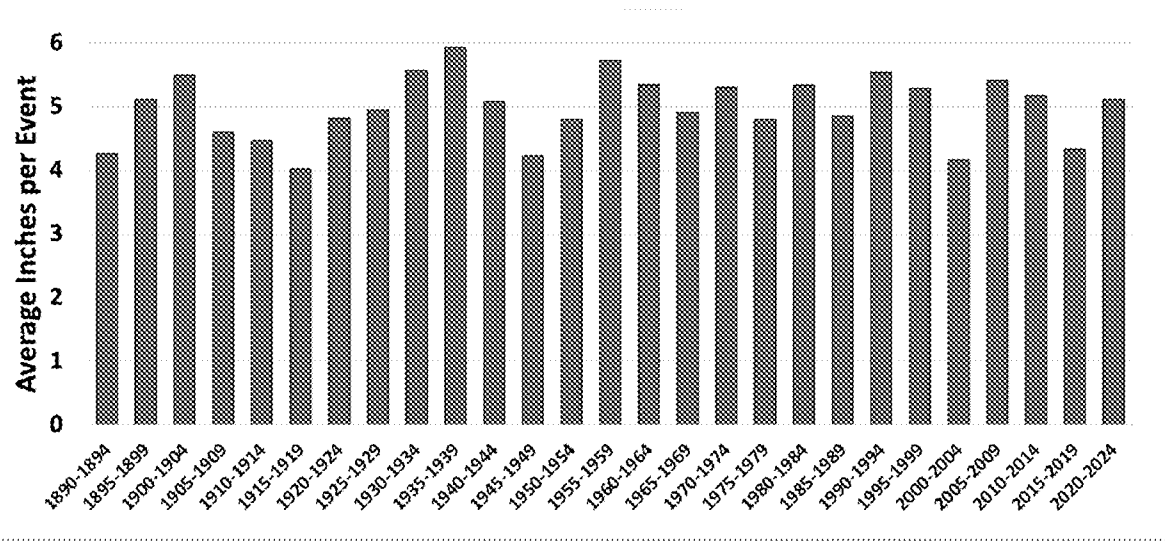


Figure 6.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.5.5.

In summary, while apparent increases in extreme precipitation events in some regions over short intervals can be found in the record, the evidence from long term, nationwide historical records does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

6.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

6.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 6.8.1, US long term data shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

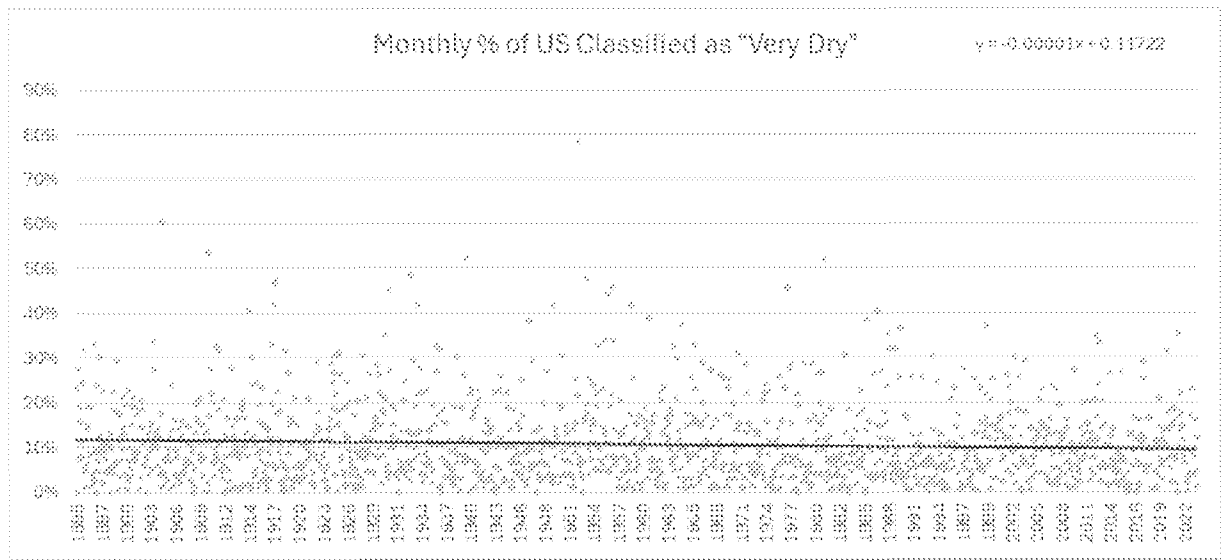


Figure 6.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: "it is possible to state firmly that global and main grain countries' drought area and intensity trends have not been following global climate warming since 1980's."

6.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 6.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.9.2.

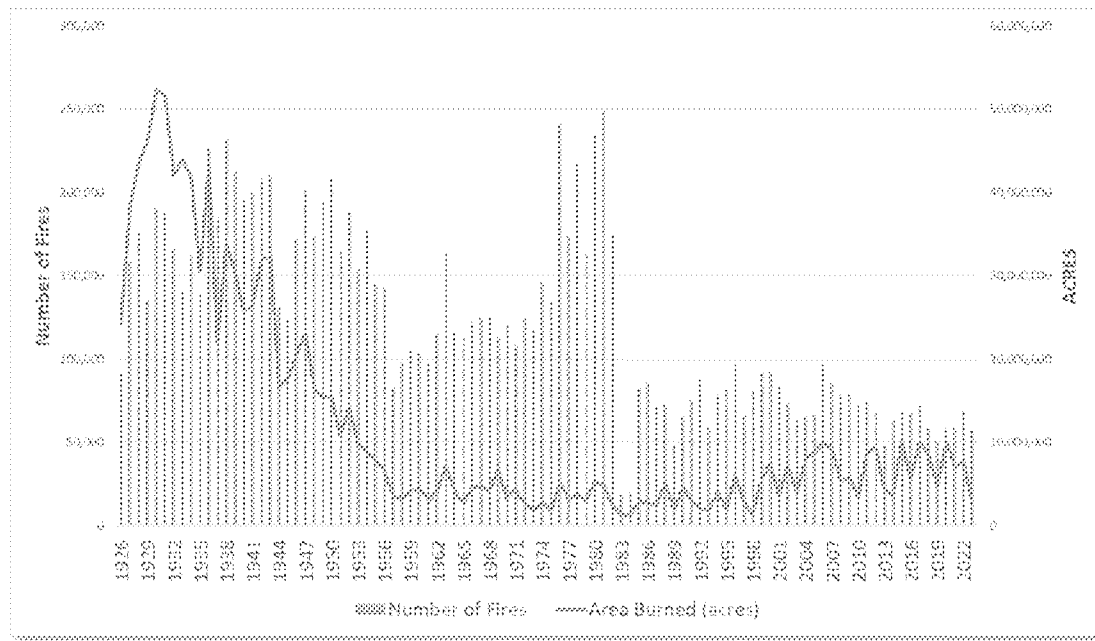


Figure 6.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Centre data Pre-2017 webarchive.org.

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and

controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

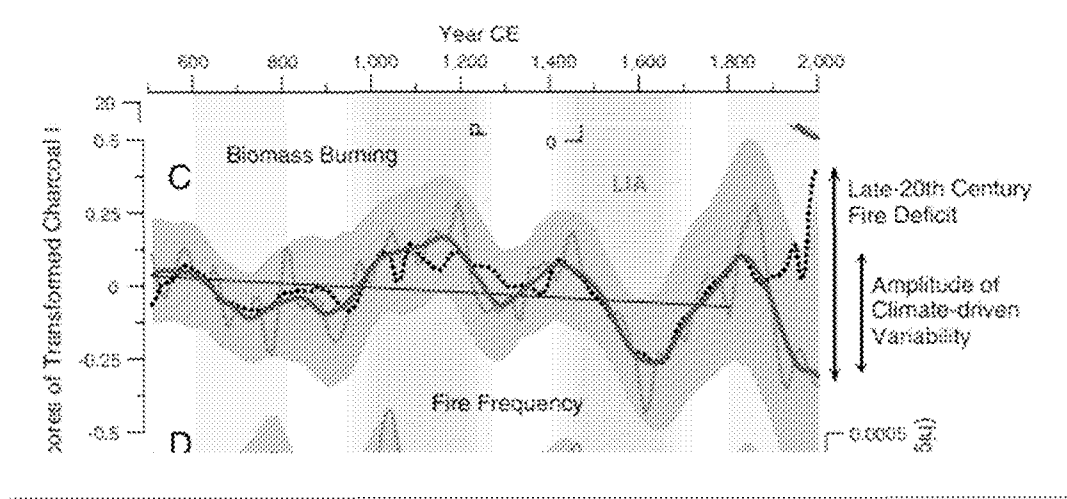


Figure 6.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

6.10 Summary

Contrary to popular belief and frequent claims by the media and many political leaders, most types of extreme weather exhibit no statistically significant trends, nor do assessment reports of the IPCC or the NCA claim to have detected any. There has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, but a decrease relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term trends are not detectable. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfire activity has increased in the US in recent decades but has declined globally and in the US is down significantly relative to the early 20th century and to the estimated natural baseline level. Changes in US wildfire activity are strongly affected by changing forest fire management practices.

References

- Brewer, W., *Up and Down California in 1860–1864 The Journal of William H. Brewer* (Berkley, CA: University of California Press, 1930).
- Christy, J.R. W. Norris and R.T. McNider, 2009. Surface temperature variations in East Africa and possible causes. *J. Climate*, 22, 3342–3356. DOI: 10.1175/2008JCLI2726.1.
- Cohn, Timothy A., Lins, Harry F. (2005). Nature's style: naturally trendy. *Geophys. Res. Lett.* 32. <https://doi.org/10.1029/2005GL024476>.
- Gershunov, A. and K. Guirguis, 2012. California heat waves in the present and future. *Geophys. Res. Lett.* <https://doi.org/10.1029/2012GL052979>
- Gershunov, A., Shulgina, T., Ralph, F. M., Lavers, D. A. & Rutz, J. J. Assessing the climate-scale variability of atmospheric rivers affecting western North America. *Geophys. Res. Lett.* **44**, 7900–7908 (2017).
- Howarth, M.E., C.D. Thorncroft and L.F. Bosart, 2019, Changes in extreme precipitation in the Northeast United States: 1979–2014. *J. Hydromet.* 20, 673–689. DOI: 10.1175/JHM-D-18-0155.1
- Hurst, H. E. (1951), Long term storage capacities of reservoirs, *Trans. Am. Soc. Civ. Eng.*, 116, 776–808.
- Jong, B.-T., Murakami, H., Delworth, T. L., & Cooke, W. F. (2024). Contributions of tropical cyclones and atmospheric rivers to extreme precipitation trends over the Northeast US. *Earth's Future*, 12, e2023EF004370. <https://doi.org/10.1029/2023EF004370>
- Karl, T.R., C.N. Williams, Jr., F.T. Quinlan, and T.A. Boden, 1990: United States Historical Climatology Network (HCN) Serial Temperature and Precipitation Data, Environmental Science Division, Publication No. 3404, Carbon Dioxide Information and Analysis Center, Oak Ridge National Laboratory, Oak Ridge, TN, 389 pp.
- Markonis, Yannis, Koutsoyiannis, Demetris (2016). Scale-dependence of persistence in precipitation records. *Nat. Clim. Change* 6, 399–401.
- Mass, C., D. Owens, J. Christy, and R. Conrick, **2024**: The Pacific Northwest heat wave of 25–30 June 2021: Synoptic/Mesoscale conditions and climate perspective. *Weather and Forecasting*, 39. DOI: 10.1175/WAF-D-23-0154.1.
- McKittrick, R. and J.R. Christy, **2019**: Assessing changes in US regional precipitation on multiple time scales. *J. Hydro.* 578, (2019), DOI.ORG/10.1016/j.jhydrol.2019.124074
- Overland, J. E., 2021: Causes of the record-breaking Pacific Northwest heatwave, late June 2021. *Atmosphere*, **12**, 1434, <https://doi.org/10.3390/atmos12111434>.
- NCA17, Climate Science Special Report: Fourth National Climate Assessment, Volume I, 2017. Wuebbles, D.J., D.W. Fahey and K.A. Hibbard .eds. U.S. Global Change Research Program. Washington DC, USA. doi: 10.7930/J0J964J6. <https://repository.library.noaa.gov/view/noaa/19486>

NCA23, Fifth National Climate Assessment. Crimmins, A.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, B.C. Stewart, and T.K. Maycock, Eds. U.S. Global Change Research Program, Washington, DC, USA. <https://doi.org/10.7930/NCA5.2023.CH1>.

Null, J. and J. Hulbert, "California Washed Away: The Great Flood of 1862," *Weatherwise* 60, no. 1 (2007): 26–30, <https://doi.org/10.3200/wewi.60.1.26-30>.

Pan, M., M. Lu and U. Lall, 2024: Diversity of cross-Pacific atmospheric river main routes. *Nature Com. Earth & Envi.* 5., 378. <https://www.nature.com/articles/s43247-024-01552-y>

Philip, S. Y., Kew, S. F., van Oldenborgh, G. J., Anslow, F. S., Seneviratne, S. I., Vautard, R., Coumou, D., Ebi, K. L., Arrighi, J., Singh, R., van Aalst, M., Pereira Marghidan, C., Wehner, M., Yang, W., Li, S., Schumacher, D. L., Hauser, M., Bonnet, R., Luu, L. N., Lehner, F., Gillett, N., Tradosky, J. S., Vecchi, G. A., Rodell, C., Stull, R. B., Howard, R., and Otto, F. E. L.: Rapid attribution analysis of the extraordinary heat wave on the Pacific coast of the US and Canada in June 2021, *Earth Syst. Dynam.*, 13, 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>, 2022.

Porter, K. et al., *Overview of the Arkstorm Scenario* (Reston, VA: Dept. of the Interior. U.S. Geological Survey, 2011).

Pielke, R. A. et al. Land use/land cover changes and climate: Modeling analysis and observational evidence. *Wiley Interdiscip. Rev. Clim. Chang.* 2, 828–850 (2011).

Quinlan, F. T., T. R. Karl, and C. N. Williams Jr. (1987), United States Historical Climatology Network (USHCN) serial temperature and precipitation data, NDP-019, Carbon Dioxide Inf. Anal. Cent., Oak Ridge Natl. Lab., U.S. Dep. of Energy, Oak Ridge, Tenn.

USGCRP, 2023: USGCRP Indicators Platform: Heat Waves. U.S. Global Change Research Program. <https://www.globalchange.gov/indicators/heat-waves>

White, R.H., Anderson, S., Booth, J.F. *et al.* The unprecedented Pacific Northwest heatwave of June 2021. *Nat Commun* 14, 727 (2023). <https://doi.org/10.1038/s41467-023-36289-3>

Weinkle, Jessica, Ryan Maue and Roger Pielke Jr. (2012) Historical Global Tropical Cyclone Landfalls *Journal of Climate* 25(13) 4729–4735 <https://doi.org/10.1175/JCLI-D-11-00719.1>

Tu, Shifei, Zhenzhen Hu, Mei Liang, Wen Zhou, Johnny Chan and Jianjun Xu (2024) Decreasing trend in destructive potential of tropical cyclones in the South Indian Ocean since the mid-1990s. *Communications Earth and Environment* 5:543 <https://www.nature.com/articles/s43247-024-01683-2>

Yang, L., Yang, Y., Shen, Y. *et al.* Urban development pattern's influence on extreme rainfall occurrences. *Nat Commun* 15, 3997 (2024). <https://doi.org/10.1038/s41467-024-48533-5>.

Zhang, W., Villarini, G., Vecchi, G. A. & Smith, J. A. Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. *Nature* 563, 384–388 (2018).

1. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge, UK:

- Cambridge University Press, 2021), Chapter 11, <https://www.ipcc.ch/report/ar6/wg1/chapter/chapter-11/>.
2. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021: The Physical Science Basis. Summary for Policymakers*, in *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2023), <https://www.cambridge.org/core/books/climate-change-2021-the-physical-science-basis/summary-for-policymakers/8E7A4E3AE6C364220F3B76A189CC4D4C>.
 3. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021*.
 4. Ryan N. Maue, *Climatlas: Tropical Cyclones*, accessed May 8, 2025, <https://climatlas.com/tropical/>.
 5. Colorado State University, *Realtime Tropical Cyclone Guidance*, Tropical Weather and Climate Research, Department of Atmospheric Science, accessed May 8, 2025, <https://tropical.atmos.colostate.edu/Realtime/index.php>.
 6. Gabriel A. Vecchi and Thomas R. Knutson, "Estimating Annual Numbers of Atlantic Hurricanes Missing from the HURDAT Database (1878–1965) Using Ship Track Density," *Journal of Climate* 24, no. 6 (2011): 1736–1746, <https://doi.org/10.1175/2010JCLI3810.1>.
 7. National Hurricane Center, *Tropical Cyclone Climatology*, National Oceanic and Atmospheric Administration, accessed May 8, 2025, <https://www.nhc.noaa.gov/climo/images/AtlanticStormTotalsTable.pdf>.
 8. Stanley B. Goldenberg et al., "The Recent Increase in Atlantic Hurricane Activity: Causes and Implications," *Science* 293, no. 5529 (July 20, 2001): 474–479, <https://doi.org/10.1126/science.1060040>.
 9. Gerald D. Bell and Muthuvel Chelliah, "Leading Tropical Modes Associated with Interannual and Multidecadal Fluctuations in North Atlantic Hurricane Activity," *Journal of Climate* 19, no. 4 (February 15, 2006): 590–612, <https://doi.org/10.1175/JCLI3659.1>.
 10. Philip J. Klotzbach et al., "Continental U.S. Hurricane Landfall Frequency and Associated Damage: Observations and Future Risks," *Bulletin of the American Meteorological Society* 99, no. 7 (July 2018): 1359–1376, <https://doi.org/10.1175/BAMS-D-17-0184.1>.
 11. NOAA Hurricane Research Division(a), *All U.S. Hurricanes (1851–2019)*, Atlantic Oceanographic and Meteorological Laboratory, National Oceanic and Atmospheric Administration, accessed May 8, 2025, https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html.
 12. Philip J. Klotzbach et al., "Continental U.S. Hurricane Landfall Frequency and Associated Damage."
 13. Gabriele Villarini, Gabriel A. Vecchi, and James A. Smith, "U.S. Landfalling and North Atlantic Hurricanes: Statistical Modeling of Their Frequencies and Ratios," *Monthly Weather Review* 140, no. 1 (January 2012): 44–65, <https://doi.org/10.1175/MWR-D-11-00063.1>.
 14. NOAA Hurricane Research Division(b), *Most Intense (3, 4, 5) Continental United States Hurricanes: 1851 - 1970, and 1983-2023*, Atlantic Oceanographic and Meteorological Laboratory, National Oceanic and Atmospheric Administration, accessed May 8, 2025, https://www.aoml.noaa.gov/hrd/hurdat/most_intense.html.

Charles Apple, "1910 Fire - the Big Burn across Montana and Idaho," *Spokesman.com* (The Spokesman-Review, January 21, 2020), <https://www.spokesman.com/stories/2020/jan/19/1910-fire-big-burn-across-montana-and-idaho/>.

National Forest Foundation "Blazing Battles: The 1910 Fire and Its Legacy," National Forest Foundation, accessed September 28, 2022, <https://www.nationalforests.org/our-forests/your-national-forests-magazine/blazing-battles-the-1910-fire-and-its-legacy>.

Forest History Society "The 1910 Fires," Forest History Society, accessed September 28, 2022, <https://foresthistory.org/research-explore/us-forest-service-history/policy-and-law/fire-u-s-forest-service/famous-fires/the-1910-fires/>.

US Forest Service (2022) "Managing Fire," US Forest Service, September 28, 2022, <https://www.fs.usda.gov/science-technology/fire>.

Lauren Sommer (2016), "Let It Burn: The Forest Service Wants to Stop Putting out Some Fires," KQED, November 7, 2016, <https://www.kqed.org/science/1134217/let-it-burn-the-forest-service-wants-to-stop-putting-out-some-fires>.

Stephens, Scott L et al., (2021) "Fire, Water, and Biodiversity in the Sierra Nevada: A Possible Triple Win," *Environmental Research Communications* 3, no. 8 (August 6, 2021): p. 081004, <https://doi.org/10.1088/2515-7620/ac17e2>.

Webarchive.org (nd) Archive of NIFC fire data [https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo stats totalFires.html](https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo%20stats%20totalFires.html).

National Interagency Fire Center (2024) Wildfire statistics. <https://www.nifc.gov/fire-information/statistics/wildfires>

7 Changes in Sea level

Arguably the most important climate impact driver that is unambiguously associated with increasing temperatures is global sea level rise. Global warming increases sea level rise through thermal expansion of the volume of sea water and melting of glaciers and ice sheets. Another factor that influences sea level variations is land water storage. Regional sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Local sea level rise is further influenced by vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018. The rate of sea level rise has accelerated in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018.¹ The rate of global sea level rise is estimated to be 0.12 inches/year (for reference: 0.12 in is the height of two stacked pennies).²

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

7.1 U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise may have little relevance for specific locations³. In Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast has rates of sea level rise of 0 to 0.12 inches/year. The largest rates of sea level rise are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the rise in the volume of seawater with local vertical land motion. Hence in examining local sea level changes, it is important to also consider the local vertical land motion. Absolute local sea level rise is the sum of relative sea level rise and the local vertical land motion.

A wide range of processes can cause vertical land motion along the coasts, having amplitudes comparable to the sea level signals expected from land-ice melting or ocean thermal expansion. Vertical land motion on the coasts can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise. Local changes in sea level vary considerably from place to place and can

¹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.

² “Rising Waters: How NASA Is Monitoring Sea Level Rise,” NASA (NASA), accessed May 19, 2022, <https://www.nasa.gov/specials/sea-level-rise-2020/>.

³ <https://tidesandcurrents.noaa.gov/sltrends/>

deviate substantially from the rate of global mean sea level change.⁴ Human activities triggering subsidence are soil drainage (e.g. for urban development purposes) or subsurface mining of resources such as groundwater, oil or gas. The magnitude of relative sea level rise caused by human activities is often considerable. Local vertical land motion of relevance to local sea level change is best measured using a Global Positioning System (GPS) station located in the location as the tide gauge.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR)⁵ and the vertical land motion (VLM)^{6, 7,8} measurements. The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local sinking of the land. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Table 7.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.1). As shown in Table 7.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent rate of absolute sea level rise of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year.⁹ Landfill zones are sinking due to soil compaction, at a rate as much as one-half inch per year, threatening coastal infrastructure including the San Francisco International Airport. The problems in the San Francisco Bay area have been caused primarily by sinking in landfill regions that were formerly wetlands, not by the slow creep of global sea level rise.

⁴ Wöppelmann, G., and M. Marcos (2016), Vertical land motion as a key to understanding sea level change and variability, *Rev. Geophys.*, 54, 64–92.

⁵ NOAA Tides & Currents, Relative Sea Level Trends - <https://tidesandcurrents.noaa.gov/sltrends/>

⁶ NAS (2012) *Sea-Level Rise for the Coasts of California, Oregon and Washington: Past, Present, and Future*. Appendix A: Vertical Land Motion and Sea-Level Data Along the West Coast of the United States. National Academies Press, NAP.edu/10766.

⁷ Letetrel, C, M Karpytchev, MN Bouin et al (2015) Estimation of vertical land movement rates along the coasts of the Gulf of Mexico over the past decades. *Continental Shelf Research*, 111, 42-51.

⁸ Karegar, MA, TH Dixon, SE Engelhart (2016), Subsidence along the Atlantic Coast of North America: Insights from GPS and late Holocene relative sea level data, *Geophys. Res. Lett.*, 43, 3126–3133, doi:10.1002/2016GL068015.

⁹ Shirzaei, M, R Burgmann (2018) Global climate change and local land subsidence exacerbate inundation risk to the San Francisco Bay Area. *Science Advances*, 4, eaap9234

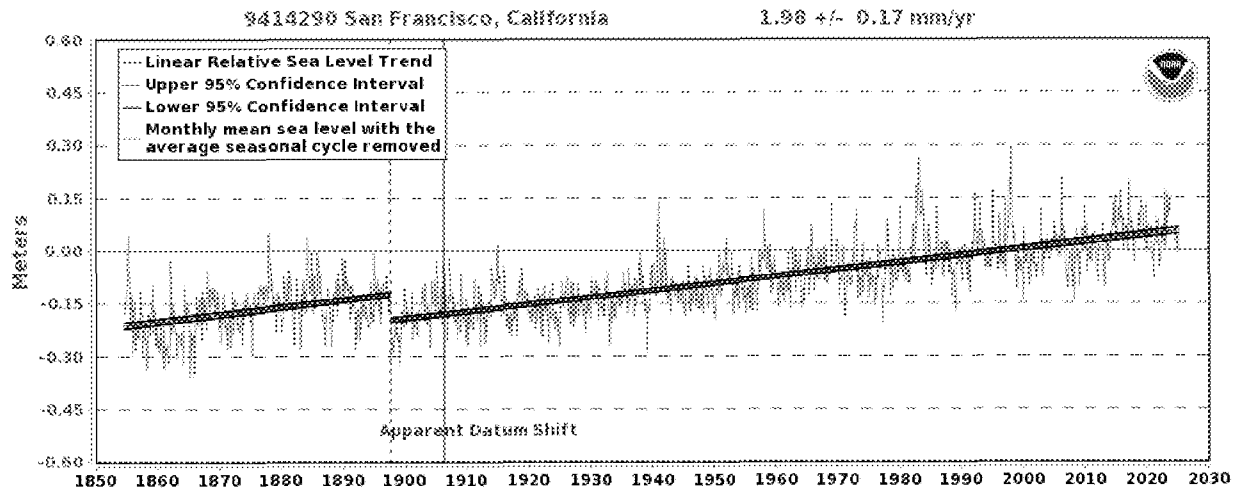


Figure 7.1. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.2). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding a value of absolute sea level rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region has occurred as a direct result of groundwater withdrawals.¹⁰ This caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes are traditionally the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the United States' deadliest natural disaster.¹¹ Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula literally removing significant portions of the land mass.¹² While only 17 people were killed in Texas, property damage exceeded \$50 billion.¹³ In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages.¹⁴

¹⁰ Kasmarek, M.C., and Ramage, J.K., 2017, Water-level altitudes 2017 and water-level changes in the Chicot, Evangeline, and Jasper aquifers and compaction 1973–2016 in the Chicot and Evangeline aquifers, Houston-Galveston region, Texas: U.S. Geological Survey Scientific Investigations Report 2017–5080, 32 p., <https://doi.org/10.3133/sir20175080>.

¹¹ Weems, John Edward, "Galveston Hurricane of 1900", Texas State Historical Association, (March 15, 2016) <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.

¹² "Galveston County, Texas, Faces Sea Level Rise and Storms", Union of Concerned Scientists, (June 23, 2017) <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.

¹³ White, Audrey, "Galveston Still Healing 5 Years After Hurricane Ike", The Texas Tribune, (April 26, 2013) <https://www.texastribune.org/2013/04/26/galveston-still-healing-5-years-after-hurricane-ike/>.

¹⁴ NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

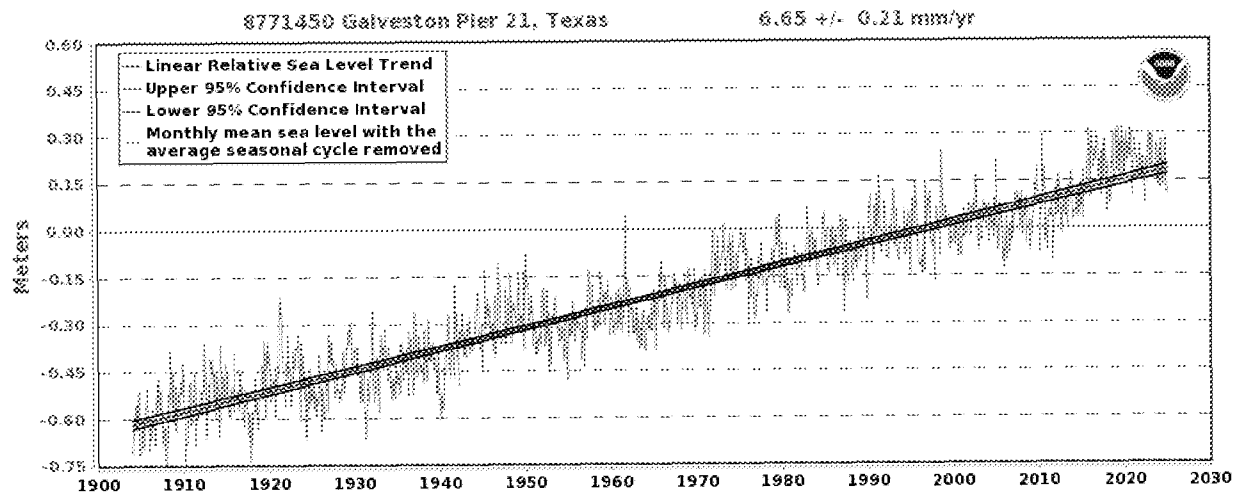


Figure 7.2. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

There are long-term tide gauge measurements at Grand Isle, Louisiana, respectively estimating that sea level has risen slightly more than 3 feet over the last 100 years and at an average rate of 0.36 inches/year (Figure 8.3). Vertical land motion (subsidence) is estimated -0.28 inches/year at Grand Isle. From Table 6.1, the absolute sea level rise is +0.08 inches/year at Grand Isle.

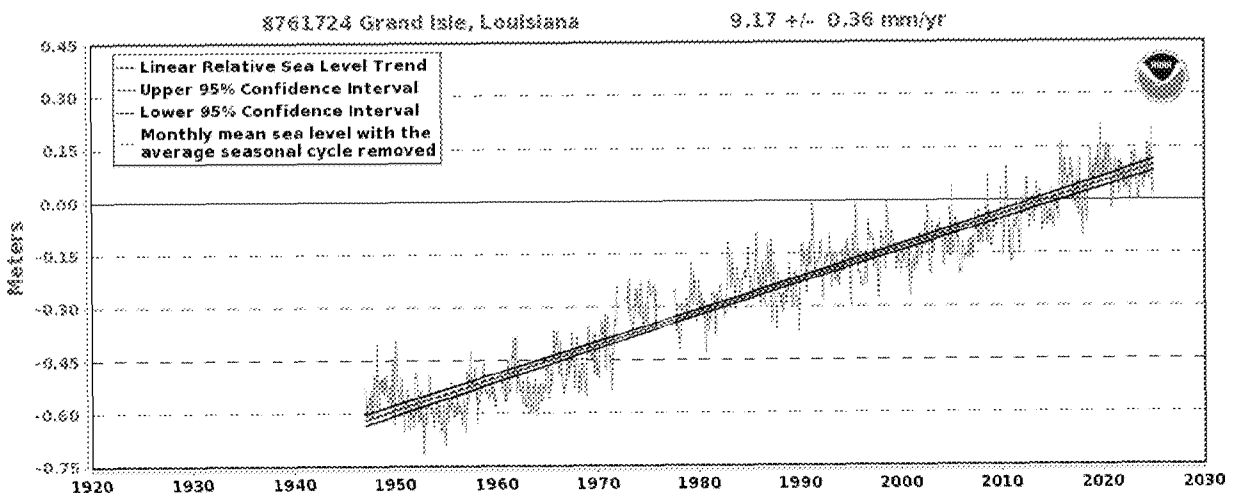


Figure 7.3. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. Due to the construction of dams in the basin since the 1950s, the suspended

sediment load of the Mississippi River has decreased by ~50%.¹⁵ A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year.¹⁶ For a city whose elevation averages one to two feet below sea level, sea level rise from human caused warming is not the dominant driver for the problems that New Orleans is facing.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. In New York City, relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 8.4). Vertical land motion in the New York City area is occurring at a rate of -0.05 inches/year (subsidence), corresponding to roughly 5 inches per century. From Table 7.1, the absolute rate of sea level rise at The Battery location is 0.06 inches/year, or about 55% of the measured relative sea level rise.

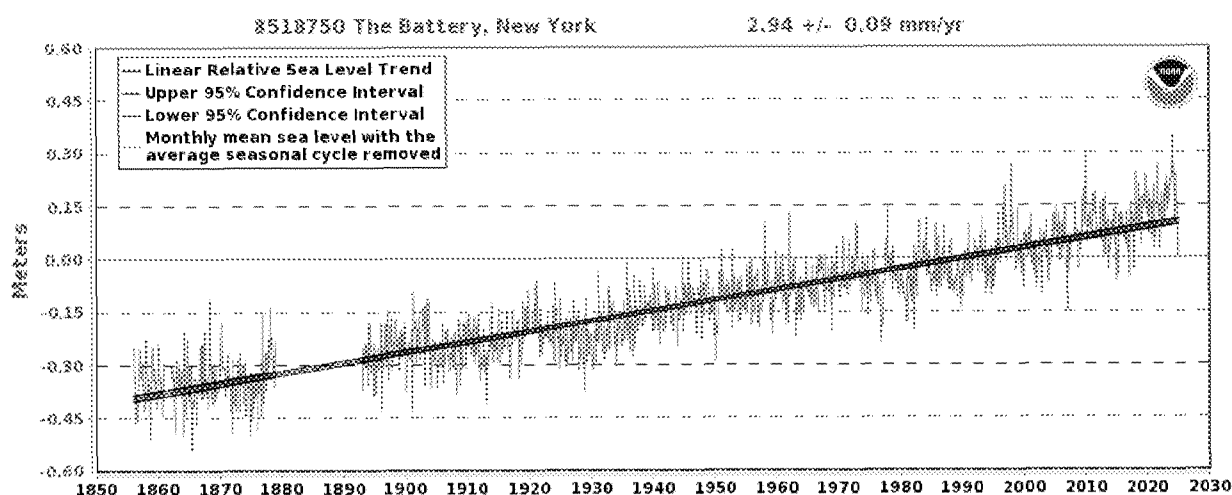


Figure 7.4. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Hurricane Sandy, New York has developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York*.¹⁷ A broad range of coastal protection measures are outlined that match the risks facing a given area: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

¹⁵ Jillian M. Maloney et al., “Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation,” *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.

¹⁶ Jaap H. Nienhuis et al., “A New Subsidence Map for Coastal Louisiana,” *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.

¹⁷ City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.

7.2 Sea level rise projections

The concern over sea level rise is not about the 8 inches or so that global mean sea level has risen since 1900. Rather, the concern is about projections of 21st century sea level rise based on climate model-based projections of human-caused global warming.

The IPCC AR6 finds that there is *high agreement* across published global mean sea level projections for 2050 and there is little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period.¹⁸

Conversely, there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5.¹⁹ There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 8.1–8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

7.3 Summary

Since 1900, global average sea level has risen by about 8". Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. From the tide gauge measurements in Figures 7.1–7.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

¹⁸ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211–1362.

¹⁹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change.”

8 Uncertainties in Climate Change Attribution

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause.¹ As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement:

¹ Note that the IPCC definition of “climate change” allows for both natural and human causes. This differs from the UNFCCC definition (and common usage), where the term is limited to human causes.

(Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 5, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. This minimal contribution of natural variability has been disputed by a number of publications that question the magnitudes of solar variability and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is

higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large

relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the

timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999)

methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called

vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest when assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first column of Table 12.12 in Ranasinghe et al. (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	3
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fire weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	13
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease
Medium confidence of decrease
Low confidence in direction of change
Medium confidence of increase
High confidence of increase

Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

Out of the 33 weather impact categories an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Columns 2 and 3 of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We omitted these columns in part because they refer to whether climate models project signals will be detectable in the data, but this is a very different question than the one that concerns us here, namely whether a signal has been detected in historical data. Additionally, as we discuss in Chapter 3 the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Even still it is worth noting that the omitted columns in AR6 Table 12.12 indicate most weather impacts are not expected to exhibit an anthropogenic signal this century.

As we discussed in Chapter 6 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.5 Extreme event attribution (EEA)

Examining the IPCC’s treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere

- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA's tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under

the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case study from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’”

The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

8.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

1. Intergovernmental Panel on Climate Change. *IPCC Glossary*. Accessed May 2, 2025. <https://apps.ipcc.ch/glossary/>.
2. G. C. Hegerl et al., “Understanding and Attributing Climate Change,” in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 663–745.
3. J. T. Houghton et al., eds., *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press, 2001), 1–881.
4. W. Cramer et al., “Detection and Attribution of Observed Impacts,” in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. C. B. Field et al. (Cambridge: Cambridge University Press, 2014), 979–1037.
5. Intergovernmental Panel on Climate Change, *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 10.
6. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker et al. (Cambridge: Cambridge University Press, 2013), 17.
7. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2021), 10.
8. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate,” *Research in Astronomy and Astrophysics* 21, no. 6 (2021): 131, <https://doi.org/10.1088/1674-4527/21/6/131>.

9. Willie Soon et al., “The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data,” *Climate* 11, no. 9 (2023): 179, <https://doi.org/10.3390/cli11090179>.
10. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records,” *Geoscience Frontiers* 14, no. 6 (November 2023): 101650, <https://doi.org/10.1016/j.gsf.2023.101650>.
11. Gunnar Myhre et al., “Anthropogenic and Natural Radiative Forcing,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge: Cambridge University Press, 2014), 659–740, <https://doi.org/10.1017/CBO9781107415324.018>.
12. Sergey K. Gulev et al., “Changing State of the Climate System,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Geneva: Intergovernmental Panel on Climate Change, 2021), 287–422.
11. Katja Matthes et al., “Solar Forcing for CMIP6 (v3.2),” *Geoscientific Model Development* 10, no. 6 (June 22, 2017): 2247–2302, <https://doi.org/10.5194/gmd-10-2247-2017>.
12. Mike Lockwood, “Solar Influence on Global and Regional Climates,” *Surveys in Geophysics* 33, no. 3–4 (May 16, 2012): 503–534, <https://doi.org/10.1007/s10712-012-9181-3>.
13. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate.”
14. Nicola Scafetta et al., “Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018,” *Remote Sensing* 11, no. 21 (November 1, 2019): 2569, <https://doi.org/10.3390/rs11212569>.
14. V. M. Velasco Herrera, B. Mendoza, and G. Velasco Herrera, “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
15. Theodosios Chatzistergos, Natalie A. Krivova, and Kok Leng Yeo, “Long-Term Changes in Solar Activity and Irradiance,” *Journal of Atmospheric and Solar-Terrestrial Physics* 252 (November 2023): 106150, <https://doi.org/10.1016/j.jastp.2023.106150>.
16. S. K. Solanki et al., “Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years,” *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, <https://doi.org/10.1038/nature02995>.
17. I. G. Usoskin, S. K. Solanki, and G. A. Kovaltsov, “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, <https://doi.org/10.1051/0004-6361:20077704>.
18. Werner K. Schmutz, “Changes in the Total Solar Irradiance and Climatic Effects,” *Journal of Space Weather and Space Climate* 11 (2021): 40, <https://doi.org/10.1051/swsc/2021016>.
19. Nicola Scafetta, “Discussion on Climate Oscillations: CMIP5 General Circulation Models versus a Semi-Empirical Harmonic Model Based on Astronomical Cycles,” *Earth-Science Reviews* 126 (November 2013): 321–357, <https://doi.org/10.1016/j.earscirev.2013.08.008>.
20. Frank Stefani, “Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions,” *Climate* 9, no. 11 (November 3, 2021): 163, <https://doi.org/10.3390/cli9110163>.

21. Ronan Connolly et al., “Challenges in the Detection and Attribution of Northern Hemisphere Surface Temperature Trends Since 1850,” *Research in Astronomy and Astrophysics* 23, no. 10 (2023): 105015, <https://doi.org/10.1088/1674-4527/acf18e>.
22. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records.”
24. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis*.
25. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis*.
26. Ibid.
27. J. D. McLean, C. R. de Freitas, and R. M. Carter, “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
28. Ka-Kit Tung and Jiansong Zhou, “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
29. Petr Chylek et al., “The Role of Atlantic Multi-Decadal Oscillation in the Global Mean Temperature Variability,” *Climate Dynamics* 47, no. 9–10 (February 20, 2016): 3271–3279, <https://doi.org/10.1007/s00382-016-3025-7>.
30. Nicola Scafetta, “Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature,” *Atmosphere* 12, no. 2 (2021): 147, <https://doi.org/10.3390/atmos12020147>.
31. Ross McKittrick, “Checking for Model Consistency in Optimal Fingerprinting: A Comment,” *Climate Dynamics* 58, no. 1–2 (2022): 405–411, <https://doi.org/10.1007/s00382-021-05913-7>.
32. M. R. Allen and S. F. B. Tett, “Checking for Model Consistency in Optimal Fingerprinting,” *Climate Dynamics* 15, no. 6 (1999): 419–434, <https://doi.org/10.1007/s003820050291>.
33. Ross McKittrick, Timothy Vogelsang, and John Christy, “Temperature Trends, Climate Attribution and the Nonstationarity Question,” *Earth System Dynamics Discussions* (2023): <https://doi.org/10.5194/esd-2023-11>.
34. Ross McKittrick, “Total Least Squares Bias in Climate Fingerprinting Regressions with Heterogeneous Noise Variances and Correlated Explanatory Variables,” *Environmetrics* 35, no. 2 (March 2024): e2835, <https://doi.org/10.1002/env.2835>.
35. S. Seneviratne et al., “Chapter 11: Weather and Climate Extreme Events in a Changing Climate.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
36. R. Ranasinghe et al., “Chapter 12: Climate Change Information for Regional Impact and for Risk Assessment.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1767–1926. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.014>.
37. National Academies of Sciences, Engineering, and Medicine. *Attribution of Extreme Weather and Climate Events and Their Impacts*. Washington, DC: The National Academies Press, forthcoming. <https://www.nationalacademies.org/our-work/attribution-of-extreme-weather-and-climate-events-and-their-impacts>.

38. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021: Synoptic/Mesoscale Conditions and Climate Perspective,” *Weather and Forecasting* 39, no. 2 (February 2024): 275–291, <https://doi.org/10.1175/WAF-D-23-0154.1>.
 39. World Weather Attribution. “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
 40. S.Y. Philip et al., “Rapid Attribution Analysis of the Extraordinary Heatwave on the Pacific Coast of the US and Canada June 2021,” *Earth System Dynamics* 13, no. 4 (December 8, 2022): 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>.
 41. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021.”
 42. Emily Bercos-Hickey et al., “Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave,” *Geophysical Research Letters* 49, no. 23 (December 2022): e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
 43. Judea Pearl, *Causality* (Cambridge: Cambridge University Press, 2009).
 44. Geert Jan van Oldenborgh et al., “Attributing and Projecting Heatwaves Is Hard: We Can Do Better,” *Earth’s Future* 10, no. 6 (June 2022): e2021EF002271, <https://doi.org/10.1029/2021EF002271>.
 45. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming,” NOAA Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division, 2017, <https://www.aoml.noaa.gov/hrd/Landsea/harvey-global-warming.pdf>.
 46. David M. Roth, “Tropical Cyclone Rainfall for the North Atlantic Basin,” Weather Prediction Center, National Oceanic and Atmospheric Administration, 2017, <https://www.wpc.ncep.noaa.gov/tropical/rain/tcmaxima.html>.
 47. Geert Jan van Oldenborgh et al., “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017,” *Environmental Research Letters* 12, no. 12 (December 2017): 124009, <https://doi.org/10.1088/1748-9326/aa9ef2>.
 48. Kerry Emanuel, “Assessing the Present and Future Probability of Hurricane Harvey’s Rainfall,” *Proceedings of the National Academy of Sciences* 114, no. 48 (November 28, 2017): 12681–12684, <https://doi.org/10.1073/pnas.1716222114>.
 49. Mark D. Risser and Michael F. Wehner, “Attributable Human-Induced Changes in the Likelihood and Magnitude of the Observed Extreme Precipitation During Hurricane Harvey,” *Geophysical Research Letters* 44, no. 24 (December 2017): 12,457–12,464, <https://doi.org/10.1002/2017GL075888>.
 50. Kevin E. Trenberth et al., “Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation,” *Earth’s Future* 6, no. 5 (May 2018): 730–744, <https://doi.org/10.1029/2018EF000825>.
 51. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming.”
 52. Yog Aryal et al., “Long Term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño–Southern Oscillation,” *Journal of Hydrology* 559 (2018): 698–710, <https://doi.org/10.1016/j.jhydrol.2018.02.072>.
- Ranasinghe, R., A.C. Ruane, R. Vautard, N. Arnell, E. Coppola, F.A. Cruz, S. Dessai, A.S. Islam, M. Rahimi, D. Ruiz Carrascal, J. Sillmann, M.B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul, (2021): Climate Change Information for Regional Impact and for Risk Assessment. In *Climate Change 2021*:

The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1767–1926, doi:[10.1017/9781009157896.014](https://doi.org/10.1017/9781009157896.014).

Jones, Gareth, Peter A. Stott and John F.B. Mitchell (2016) Uncertainties in the Attribution of Greenhouse Gas Warming and Implications for Climate Prediction. *Journal of Geophysical Research-Atmospheres* 121(12) 6969–6992 <https://doi.org/10.1002/2015JD024337>.

Kravtsov, S., A. Westgate and A. Gavrilov (2024) Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics* Volume 62, pages 10281–10306 <https://link.springer.com/article/10.1007/s00382-024-07451-4>

Weinkle, Jessica (2025) Carnival mirrors: How concentrated is the event attribution literature? Substack essay <https://jessicaweinkle.substack.com/p/how-big-is-the-event-attribution>

Chen, Chung and Lon-Mu Liu (1993) Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association* Vol. 88, No. 421 (Mar., 1993), pp 284–297. <http://www.jstor.org/stable/2290724>

Sardeshmukh, Prashant D., Gilbert P. Compo and Cécile Penland (2015) Need for Caution in Interpreting Extreme Weather Statistics *Journal of Climate* 28(23) 9166–9187 <https://journals.ametsoc.org/view/journals/clim/28/23/jcli-d-15-0020.1.xml>

Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 <https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>

Miralles, Ophélie and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 <https://doi.org/10.1016/j.wace.2023.100584>

Barlow, Anna Maria, Chris Sherlock and Jonathan Tawn (2020) Inference for Extreme Values Under Threshold-Based Stopping Rules. *Journal of the Royal Statistical Society Series C* August 2020, Pages 765–789, <https://doi.org/10.1111/rssc.12420>

Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. <https://doi.org/10.1029/2023GL104090>

Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. <https://blogs.oregonstate.edu/occri/oregon-climate-assessments> .

McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophysical Research Letters*, 49, e2022GL100380. <https://doi.org/10.1029/2022GL100380>

Bercos-Hickey et al. (2022) Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave. *Geophysical Research Letters* 49 <https://doi.org/10.1029/2022GL099396>

Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay
<https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>

9 Climate change and US agriculture

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptive responses of farmers are taken into account the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached similar conclusions to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming. Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a

major driver of plant growth so this omission biases the analysis towards underestimation of the benefits of climate change on agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm cause an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted US crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been

estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

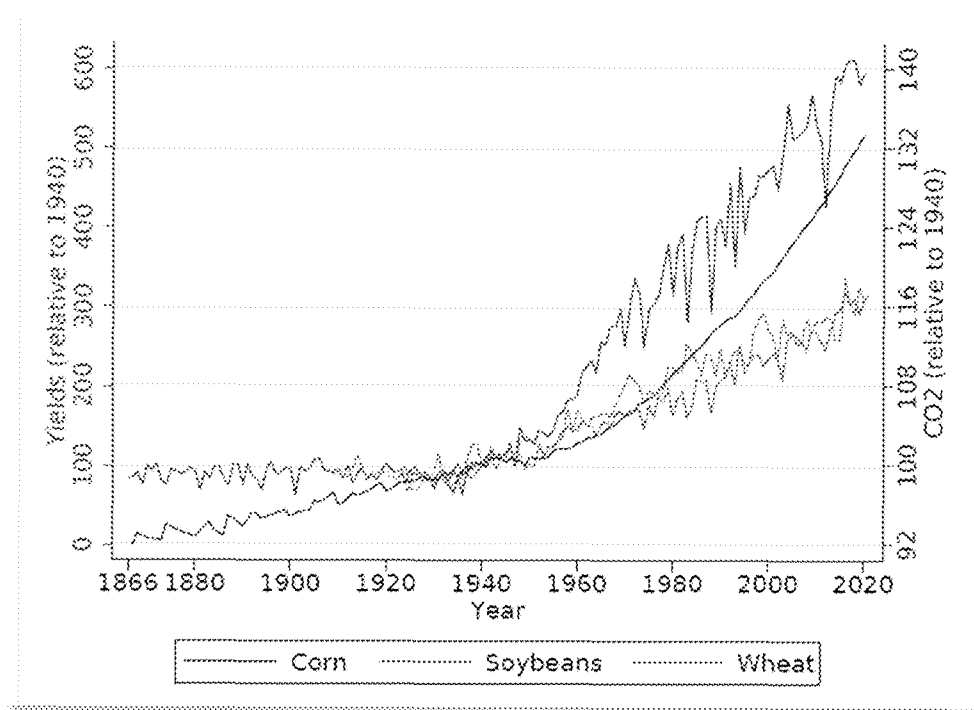


Figure 9.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100.
Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to heat. Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al. also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased

CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

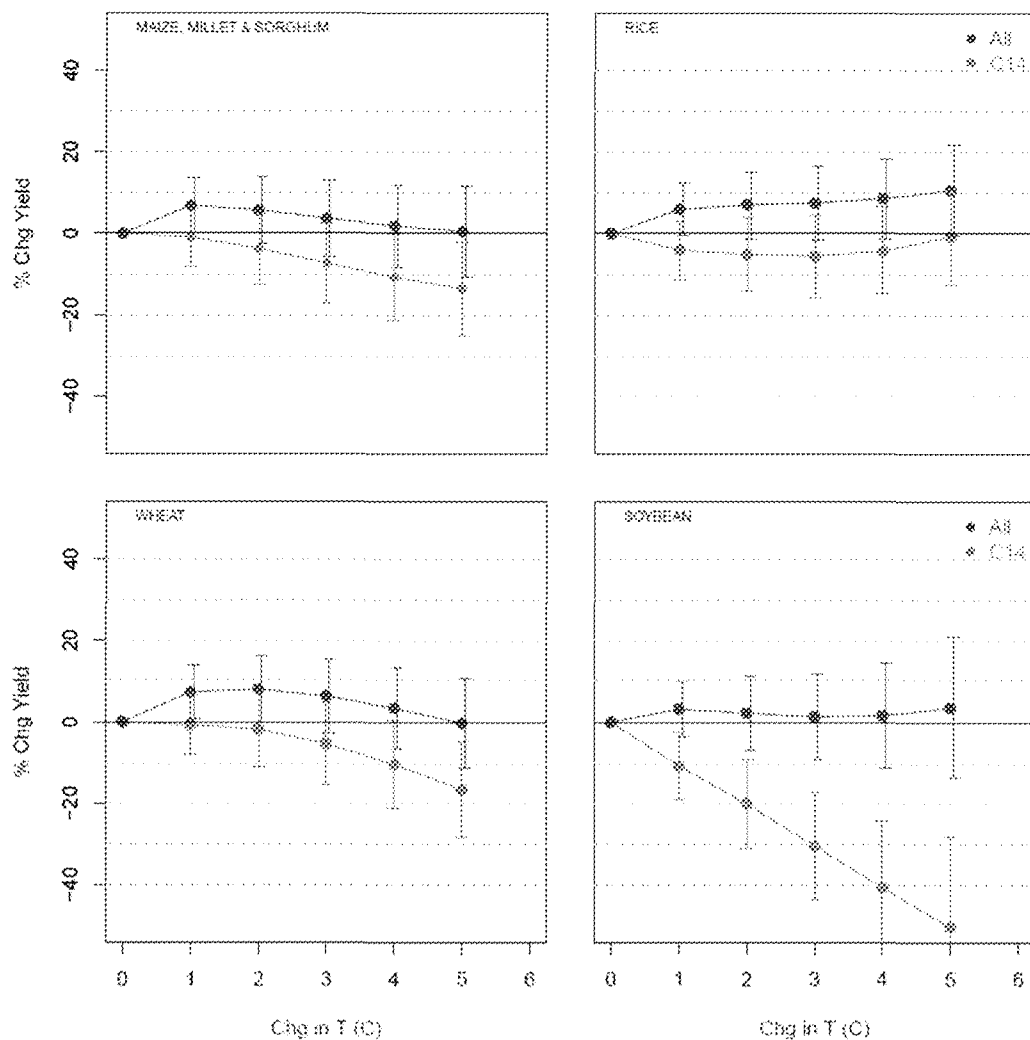


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behaviour by farmers, has been beneficial on its own for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

Deschênes, Olivier and Michael Greenstone (2007) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather *American Economic Review*. Feb 2007, Vol. 97, No. 1: Pages 354-385

Deschênes, Olivier and Michael Greenstone (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply to Comment *American Economic Review*. 102, no. 7: 3761-3773. <http://hdl.handle.net/1721.1/82641>

Ortiz-Bobea, Ariel (2019) The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture. *American Journal of Agricultural Economics*. 102 (3), 934–959.

Schlenker, Wolfram and Michael Roberts (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* 106 (37) 15594-15598 <https://doi.org/10.1073/pnas.0906865106>

10 Managing Risks of Extreme Weather

10.1 Socioeconomic context

Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020 (IM Gulkany, 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population) (NOAA, 2025; USCB, 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (T Deryugina and SM Hsiang, 2023). US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC, 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (NBER, 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA, 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (BMI, 2013). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA, 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (R Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and

wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (R Pielke Jr., 2025).

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

1. Indur M. Goklany, *Deaths from Extreme Weather Events, 1900–2010* (Washington, DC: Reason Foundation, September 2011), https://a8d50b36.delivery.rocketcdn.me/wp-content/uploads/2011/09/deaths_from_extreme_weather_1900_2010.pdf.
2. National Hurricane Center, “Costliest U.S. Tropical Cyclones Tables Updated,” *NOAA National Hurricane Center*, accessed May 8, 2025, <https://www.nhc.noaa.gov/outreach/history/>.
3. U.S. Census Bureau, Decennial Census by Decade, accessed May 8, 2025, <https://www.census.gov/programs-surveys/decennial-census/decade.html>.
4. Tatyana Deryugina and Solomon M. Hsiang, *Does the Environment Still Matter? Daily Temperature and Income in the United States*, NBER Working Paper No. 31361 (Cambridge, MA: National Bureau of Economic Research, June 2023), <https://www.nber.org/papers/w31361>.
5. National Research Council, *Adapting to the Impacts of Climate Change* (Washington, DC: The National Academies Press, 2010), <https://nap.nationalacademies.org/read/12888/chapter/2>.
6. National Bureau of Economic Research, “The Value of Improving Hurricane Forecasts,” *NBER Digest*, September 2024, <https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>.
7. Federal Emergency Management Agency (FEMA), “The Role of Florida’s Building Codes in Hurricane Michael Recovery,” last updated February 13, 2020, <https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael>.
8. Battelle Memorial Institute, *Final Independent External Peer Review Report: Hurricane Isaac (2012) Assessment*, prepared for U.S. Army Corps of Engineers, New Orleans District, December 2013, <https://www.mvn.usace.army.mil/Portals/56/docs/PD/PeerReview/TCN13-003HurrIsaacAssessIEPRFinal.pdf>.
9. Tennessee Valley Authority (TVA), *Flood Management*, accessed May 8, 2025, <https://www.tva.com/environment/managing-the-river/flood-management>.
10. American Public Power Association, “TVA Flood Mitigation Strategies Prevented Approximately \$406 Million in Potential Damages,” *Public Power Current*, March 7, 2024, <https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>.
11. Roger Pielke Jr., “Scientific Integrity and U.S. 'Billion Dollar Disasters',” *npj Natural Hazards* 1 (2024): Article 12, <https://www.nature.com/articles/s44304-024-00011-0>.
12. Roger Pielke Jr., “RIP NOAA's Billion Dollar Disasters,” *The Honest Broker (Substack)*, May 8, 2025, <https://rogerpielkejr.substack.com/p/rip-noaas-billion-dollar-disasters>.

10 Managing Risks of Extreme Weather

10.1 Socioeconomic context

Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020 (Goklany, 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population) (NOAA, 2025; USCB, 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang 2023). US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (NBER, 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA, 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (BMI, 2013). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA, 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (R Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from

publication (R Pielke Jr., 2025).

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period though not in the continental US (Chapter 6) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 20214). Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

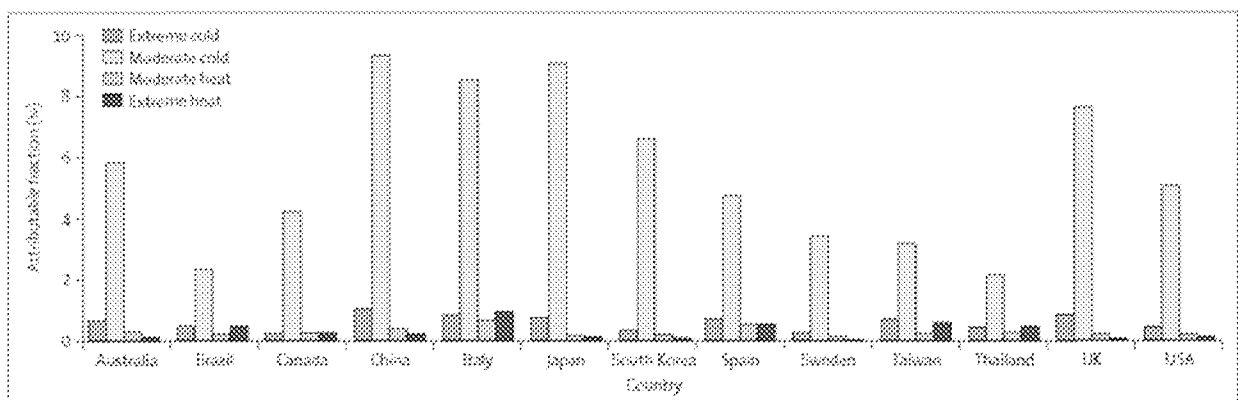


Figure 10.3.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 10.3.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities

and found a 60% decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill et al. 2022) acknowledges that heat-related mortality risk is declining over time:

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

10.3.2 The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that

“Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

10.3.3 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through

conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($>30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

10.4 Summary

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase as long as people are able to undertake adaptive responses.

1. Indur M. Goklany, *Deaths from Extreme Weather Events, 1900–2010* (Washington, DC: Reason Foundation, September 2011), https://a8d50b36.delivery.rocketcdn.me/wp-content/uploads/2011/09/deaths_from_extreme_weather_1900_2010.pdf.
2. National Hurricane Center, “Costliest U.S. Tropical Cyclones Tables Updated,” *NOAA National Hurricane Center*, accessed May 8, 2025, <https://www.nhc.noaa.gov/outreach/history/>.
3. U.S. Census Bureau, *Decennial Census by Decade*, accessed May 8, 2025, <https://www.census.gov/programs-surveys/decennial-census/decade.html>.
4. Tatyana Deryugina and Solomon M. Hsiang, *Does the Environment Still Matter? Daily Temperature and Income in the United States*, NBER Working Paper No. 31361 (Cambridge, MA: National Bureau of Economic Research, June 2023), <https://www.nber.org/papers/w31361>.
5. National Research Council, *Adapting to the Impacts of Climate Change* (Washington, DC: The National Academies Press, 2010), <https://nap.nationalacademies.org/read/12888/chapter/2>.
6. National Bureau of Economic Research, “The Value of Improving Hurricane Forecasts,” *NBER Digest*, September 2024, <https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>.
7. Federal Emergency Management Agency (FEMA), “The Role of Florida’s Building Codes in Hurricane Michael Recovery,” last updated February 13, 2020, <https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael>.
8. Battelle Memorial Institute, *Final Independent External Peer Review Report: Hurricane Isaac (2012)*

Assessment, prepared for U.S. Army Corps of Engineers, New Orleans District, December 2013, <https://www.mvn.usace.army.mil/Portals/56/docs/PD/PeerReview/TCN13-003HurrlsaacAssessIEPRFinal.pdf>.

9. Tennessee Valley Authority (TVA), *Flood Management*, accessed May 8, 2025, <https://www.tva.com/environment/managing-the-river/flood-management>.
10. American Public Power Association, “TVA Flood Mitigation Strategies Prevented Approximately \$406 Million in Potential Damages,” *Public Power Current*, March 7, 2024, <https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>.
11. Roger Pielke Jr., “Scientific Integrity and U.S. 'Billion Dollar Disasters',” *npj Natural Hazards* 1 (2024): Article 12, <https://www.nature.com/articles/s44304-024-00011-0>.
12. Roger Pielke Jr., “RIP NOAA's Billion Dollar Disasters,” *The Honest Broker (Substack)*, May 8, 2025, <https://rogerpielkejr.substack.com/p/rip-noaas-billion-dollar-disasters>.

Ritchie, Hannah (2024) - “How many people die from extreme temperatures, and how this could change in the future: Part one” Published online at OurWorldinData.org. Retrieved from: 'https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future' [Online Resource]

Zhao, Qi et al. (2021), “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

O'Neill, B et al. (2022) “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

11 Mortality from temperature extremes

11.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period though not in the continental US (Chapter 7) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions.^{1 2} Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

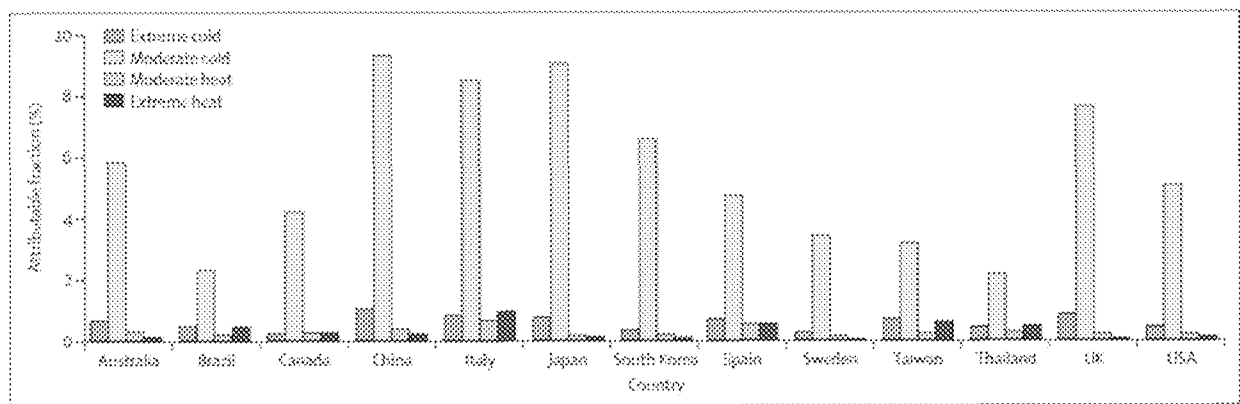


Figure 11.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 11.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

¹ Qi Zhao et al., “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

² <https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 U.S. cities and found a 60% decline in average heat-related mortality over the period 1987–2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 states how heat-related mortality is declining over time:³

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

11.2 The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that “Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting

³ B. O'Neill et al., “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

11.3 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, “Adapting to climate change: The remarkable decline in the US temperature mortality relationship over the twentieth century,” *Journal of Political Economy*, 2016, 124 (1), 105–159.

J.M. Doremus, I. Jacqz and S. Johnston (2022), “Sweating the energy bill: Extreme weather, poor households, and the energy spending gap.” *Journal of Environmental Economics and Management*, doi: <https://doi.org/10.1016/j.jeem.2022.102609> .

Nordio, Francesco, Antonella Zanobetti, Elena Colicino, Itai Kloog and Joel Schwartz (2015). “Changing patterns of the temperature–mortality association by time and location in the US, and implications for climate change” *Environment International*, Volume 81, pp 80-86 <https://doi.org/10.1016/j.envint.2015.04.009>.

Wang, Yan, Francesco Nordio , John Nairn , Antonella Zanobetti and Joel D. Schwartz (2018) “Accounting for adaptation and intensity in projecting heat wave-related mortality” *Environmental Research* 161 pp. 464—471. <https://doi.org/10.1016/j.envres.2017.11.049>

Bobb JF, Peng RD, Bell ML, Dominici F. (2014) Heat-related mortality and adaptation to heat in the United States. *Environmental Health Perspectives* 122:811–816; <https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.1307392>

Davis, Robert E., Paul C. Knappenberger, Patrick J. Michaels and Wendy M. Novicoff (2003) “Changing Heat-Related Mortality in the United States” *Environmental Health Perspectives* 111(14) November 2003 pp. 1712—1718.

Lee, Jangho and Andrew E. Dessler (2023) Future Temperature-Related Deaths in the U.S.: The Impact of Climate Change, Demographics, and Adaptation. *Geohealth* 7(8) e2023GH000799 <https://doi.org/10.1029/2023GH000799>

Allen, M.J., Sheridan, S.C. Mortality risks during extreme temperature events (ETEs) using a distributed lag non-linear model. (2018) *International Journal of Biometeorology* 62, 57–67 (2018). <https://doi.org/10.1007/s00484-015-1117-4>

13 U.S. Vehicle-Based CO₂ Emissions and the Global Climate

The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. Thus, the 2009 Endangerment Finding obligated the EPA to regulate emissions from new motor vehicles.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing US vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to how much global emissions are reduced, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0% of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating all US vehicle-based emissions would change the multidecadal warming trend by at most 3%. If we were to take into account emissions from land use and cement production, that fraction would be even smaller, but for the purpose of the following calculation, it will suffice.

For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends from five global temperature datasets range from +0.163 deg. C per decade in the NCEP/NCAR R1 reanalysis dataset to +0.211 deg. C per decade in the ERA5 reanalysis dataset. We can take this to be the range of precision with which we can estimate global warming. The latter estimate is 29% larger than the former, indicating that reduction in the rate of global warming from eliminating U.S. vehicle CO₂ emissions would be an order of magnitude below the limits of measurability. Likewise if vehicle emissions were reduced by only, say, 10 percent, the effect on the climate would be two orders of magnitude below the limits of measurement.

Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

EPA (2024) *Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions 1990-2022*. Available online at <https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P101AKR0.pdf>

Energy Institute (2024) *Statistical Review of World Energy*. Available online at <https://www.energyinst.org/statistical-review>

GLOSSARY

2XCO₂: Doubling of the atmospheric carbon dioxide (CO₂) content relative to pre-Industrial times, a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50% of the way to 2XCO₂.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The "opposite" of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science. The most recent was the AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyse economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

Climate Research Group

An Assessment of the Risks Posed by Carbon Dioxide Emissions on the United States

Report to the Secretary, US Department of Energy

May 30, 2025

John Christy, Ph.D.
Judith Curry, Ph.D.
Steven Koonin, Ph.D.
Ross McKittrick, Ph.D.
Roy Spencer, Ph.D.

Table of Contents

Secretary's Preface

Introduction: Overview and purpose of document

Part I: Direct human influence on ecosystems and the climate

- 1 Carbon dioxide and air pollution
- 2 Direct impacts of CO₂ on the environment
 - 2.1 Land- Global Greening
 - 2.2 Ocean - alkalinity
- 3 Anthropogenic Radiative forcing
 - 3.1 Components of anthropogenic radiative forcing and their history to date
 - 3.2 The carbon cycle and future emission scenarios
 - 3.3 Aerosols and the uncertainties associated with them

Part II: Climate response to CO₂ emissions

- 4 Measuring climate sensitivity to CO₂ doubling
- 5 Models versus observations in recent past
- 6 Evidence on trends and attributable changes in extreme weather
- 7 Sea level rise
- 8 Uncertainties in analysis of attribution

Part III: Impacts on ecosystems and society

- 9 Climate change and US agriculture
- 10 Managing risks of extreme weather
- 11 Mortality risk from extreme heat and cold
- 12 Climate change and the Economy
 - 12.1 Climate change and economic growth
 - 12.2 The Social Cost of Carbon
- 13 US vehicle-based CO₂ emissions and the global climate

References

Carbon dioxide as pollutant

Chapter Summary

Carbon dioxide (CO₂) is not a pollutant like the so-called Criteria Air Contaminants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

In 2006, the Supreme Court ruled that GHGs (CO₂ among them) were “pollutants” subject to regulation under Clean Air Act (Mass. V. EPA 2006). That framework defines six types of so-called Criteria Air Contaminants (EPA, undated): particulate matter, ground-level ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and carbon monoxide (CO).

While the definition of “pollutant” is ultimately a legal one, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation. In these aspects, it is similar to water.

Ambient outdoor air today contains about 420 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen *et al.* (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and also by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG), that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

Massachusetts v. EPA (2006) <https://www.oyez.org/cases/2006/05-1120>

US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. *Environmental Health Perspectives* 124(6) pp. 805-812
<https://doi.org/10.1289/ehp.1510037>

2 Direct Impacts of CO₂ on the environment

Chapter Summary

Global greening due to increased CO₂ levels in the atmosphere is well-established. CO₂ enhances photosynthesis and promotes plant growth. Increased CO₂ levels also promote water use efficiency in plants making them more drought-tolerant. Greening has been observed on every continent including arid regions and the Arctic. Earth's plants evolved under conditions of much higher CO₂ levels than at present and can be expected to continue benefiting from additional Ambient CO₂.

When CO₂ is absorbed in sea water it reduces the alkalinity of the oceans. The recent decline in alkalinity is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Declining alkalinity may adversely affect corals although the Australian Great Barrier Reef has shown considerable growth in recent years. Media attention focuses on preliminary studies that project harms from ocean acidification but experts have found a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

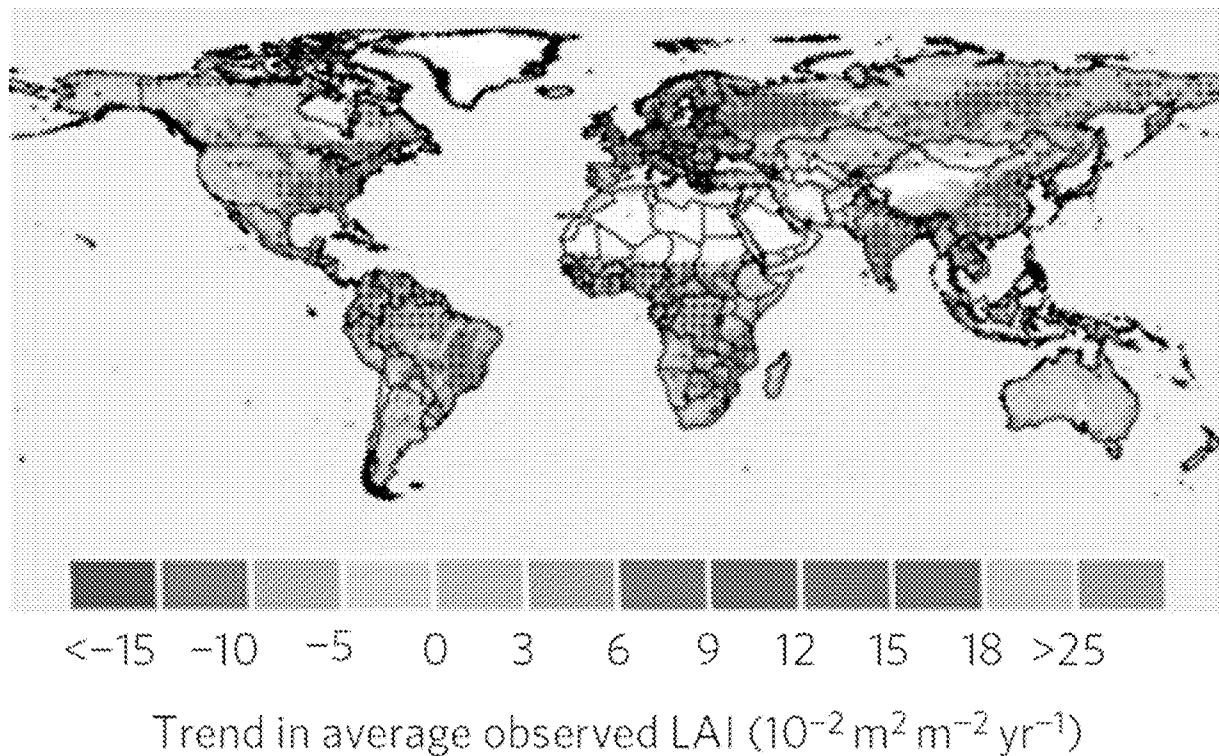


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO_2 , Haverd et al. (2020) reported a CO_2 fertilization rate nearly double what models had predicted. That is, CO_2 fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO_2 have likely understated the benefits to crops and agriculture. The connection between CO_2 fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO_2 fertilization remained the dominant driver

2.1.2 Photosynthesis and CO_2 levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO_2 is available at the surface

of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

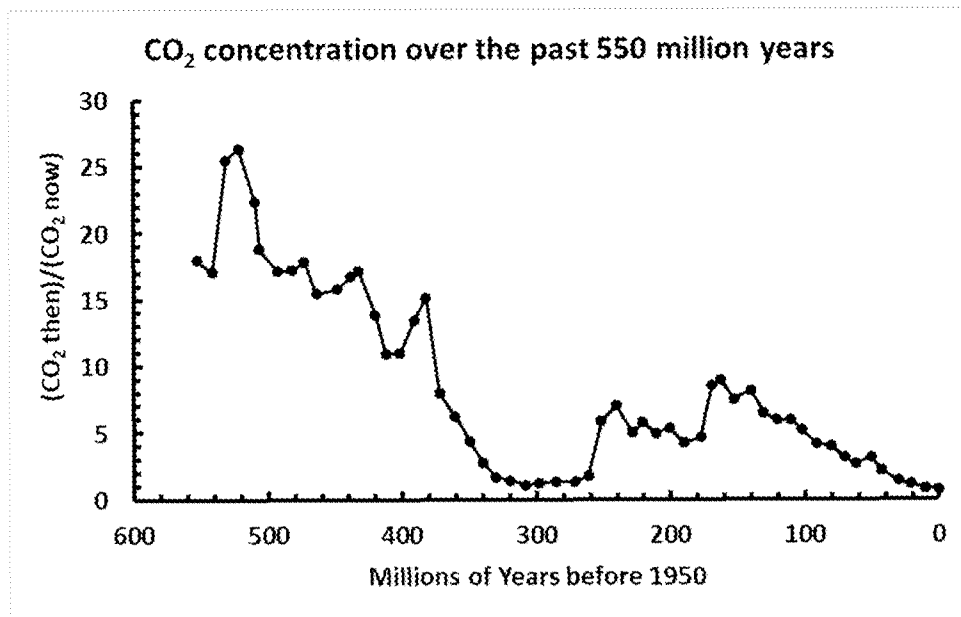


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels. Source: Adapted from Berner (2006). Current CO₂ levels correspond to about 1.3 times the indicated value at 0.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

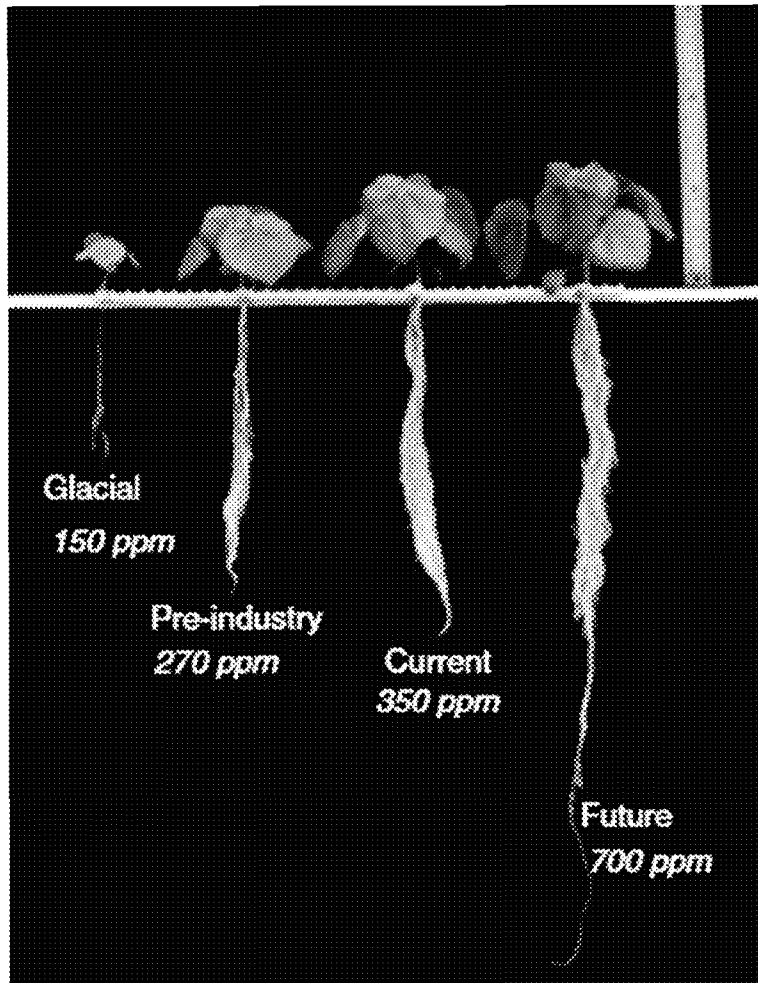


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

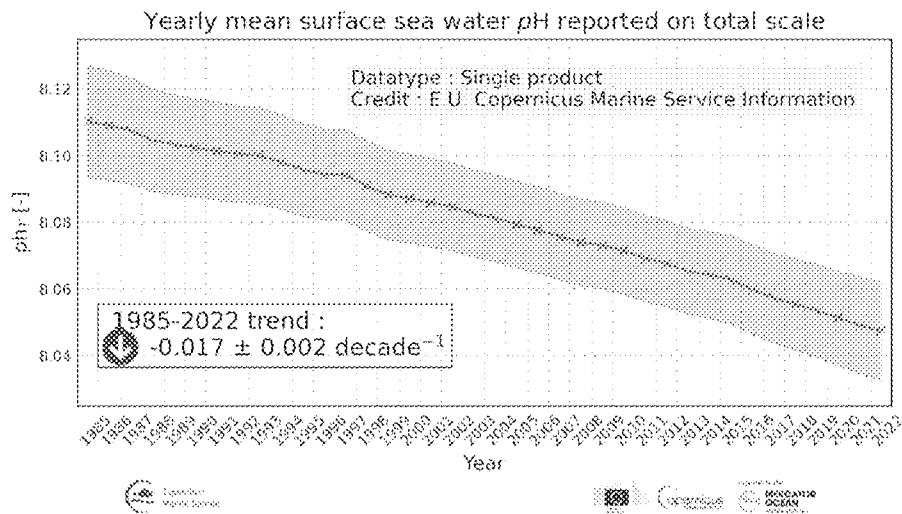


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the

results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

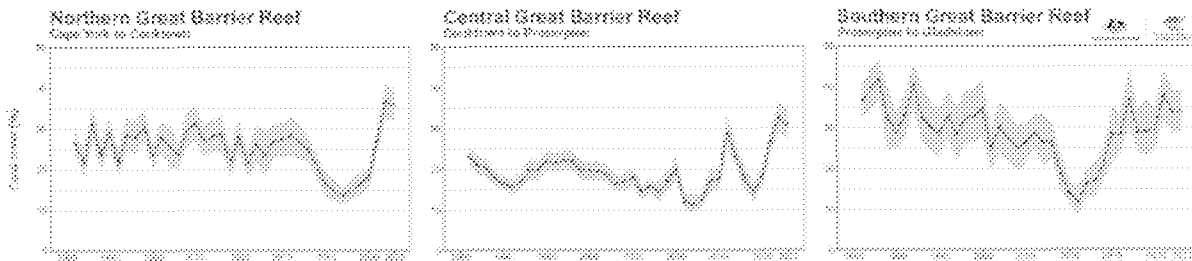


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

2.2.3 Publication bias

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An *ICES Journal of Marine Science* Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.
Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Changes to the Australian Great Barrier Reef are driven by many factors other than temperatures or alkalinity and coral cover has recently staged a major rebound. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

References

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>
- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Berner, R.A. (2006) GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
- Chen, Xin et al. (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791 <https://www.sciencedirect.com/science/article/pii/S2351989423004262>
- Cheng, L., Zhang, L., Wang, YP. et al. Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* 8, 110 (2017). <https://doi.org/10.1038/s41467-017-00114-5>
- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 18 April 2016 DOI: 10.1038/NCLIMATE2995.
- Gerhart, Laci and Joy Ward (2010) Plant responses to low [CO₂] of the past. *New Phytologist* 188:674—695. <https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>
- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* 26: 2390–2402.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, 764, 142797.
- Judd, Emily et al. (2024) A 485-million-year history of Earth's surface temperature. *Science* 385 Issue 6715 <https://doi.org/10.1126/science.adk3705>
- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, 15(10), e0241081.
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105-112.
- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, 112, 125961.
- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* 1:14-27
- Verhage, F. Y. (2017, November). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. Retrieved October 2024, from esalq: [http://www.esalq.usp.br/departamentos/leeb/eventos/Thesis Report - Fabian Verhage.pdf](http://www.esalq.usp.br/departamentos/leeb/eventos/Thesis%20Report%20-%20Fabian%20Verhage.pdf)
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* 7:432-436 May 2017 <https://www.nature.com/articles/nclimate3299>

- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 <https://www.nature.com/articles/s43247-024-01463-y>
- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* 6 Aug 2016 <https://www.nature.com/articles/nclimate3004>
- Australian Institute of Marine Science (2022). Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef. [https://www.aims.gov.au/sites/default/files/2022-08/AIMS LTMP Report on%20GBR coral status 2021 2022 040822F3.pdf](https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf)
- Beeden, R., Maynard, J., Puotinen, M., Marshall, P., Dryden, J., Goldberg, J., and Williams, G. (2015). Impacts and Recovery from Severe Tropical Cyclone Yasi on the Great Barrier Reef. *PLOS ONE*. 10. e0121272. <https://doi.org/10.1371/journal.pone.0121272>
- Browman, H. (2016). Applying organized scepticism to ocean acidification research. *iCES Journal of Marine Science: Journal du Conseil*. 73. 529.1-536. <https://doi.org/10.1093/icesjms/fsw010>
- Clements JC, Sundin J, Clark TD, Jutfelt F (2022) Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. *PLoS Biol* 20(2): e3001511. <https://doi.org/10.1371/journal.pbio.3001511>
- De'ath, G., Lough, J., and Fabricius, K. (2009). Declining Coral Calcification on the Great Barrier Reef. *Science (New York, N.Y.)*. 323. 116-9. <https://doi.org/10.1126/science.1165283>
- Gattuso, J. P. and Hansson, L. (2011). *Ocean acidification: background and history* Ocean Acidification ed J P Gattuso and L Hansson (Oxford: Oxford University Press).
- Krissansen-Totton, J., Arney, G., and Catling, D. (2018). Constraining the climate and ocean pH of the early Earth with a geological carbon cycle model. *Proceedings of the National Academy of Sciences*. 115. 201721296. <https://doi.org/10.1073/pnas.1721296115>
- Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO2 storage and release in the deep Southern Ocean on millennial to centennial timescales. *Nature*. 562. <https://doi.org/10.1038/s41586-018-0614-0>
- Revelle, R. R. and R. Fairbridge (1957). Carbonate and carbon dioxide, in *Treatise on Marine. Ecology and Paleoecology*, Vol. 1: J. W. Hedgpeth, ed.
- Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. *Marine Geology*. 346. 392-399. <https://doi.org/10.1016/j.margeo.2013.09.002>
- Woods Hole Oceanographic Institution (2023). Is the Great Barrier Reef Making a Comeback? <https://www.whoi.edu/oceanus/feature/is-the-great-barrier-reef-making-a-comeback/>
- Copernicus Marine Service (2025) Global Ocean acidification - mean sea water pH time series and trend from Multi-Observations Reprocessing. Online source [https://data.marine.copernicus.eu/product/GLOBAL OMI HEALTH carbon ph area averaged/description](https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description)
- Australia Institute of Marine Science (2023) AIMS' Annual Summary Report of Coral Reef Condition 2022/23 for the Great Barrier Reef. [https://www.aims.gov.au/sites/default/files/2023-08/QuickLook AIMS LTMP Report GBR coral status 22 23.pdf](https://www.aims.gov.au/sites/default/files/2023-08/QuickLook_AIMS_LTMP_Report_GBR_coral_status_22_23.pdf)

3 Human influences on the climate

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming. The modern record is uncertain in part due to an interruption in satellite coverage following the 1986 Space Shuttle Challenger disaster.

Climate projections are based on IPCC emission scenarios which have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading. Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth’s energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms

while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

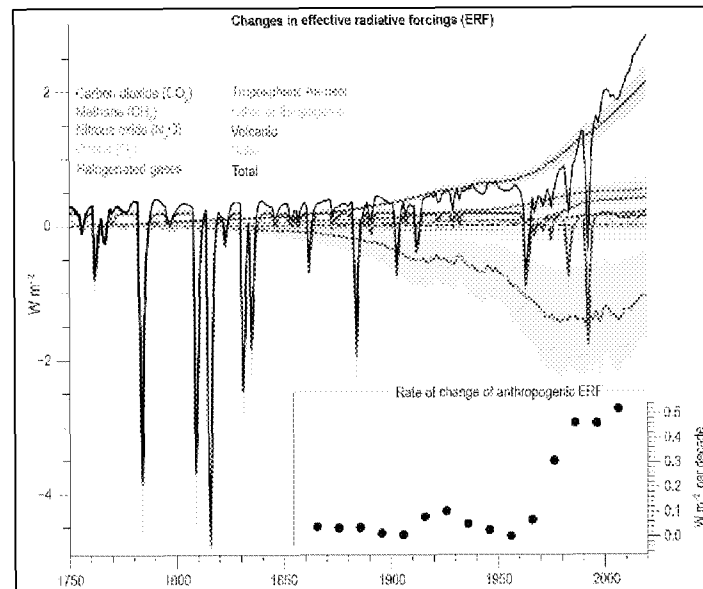


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

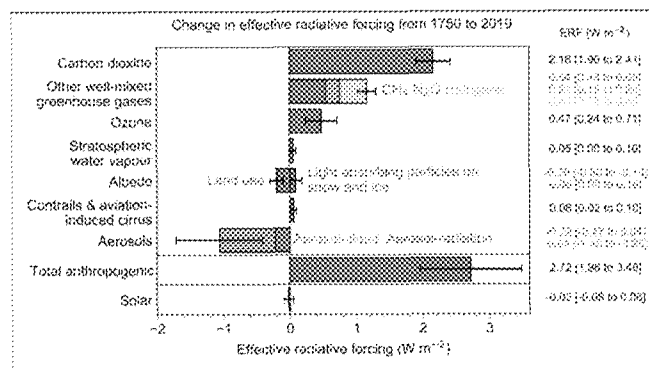


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO_2 are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing.

Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how that gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

3.1.2 Urban heat islands and land use change

3.1.3 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration above 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

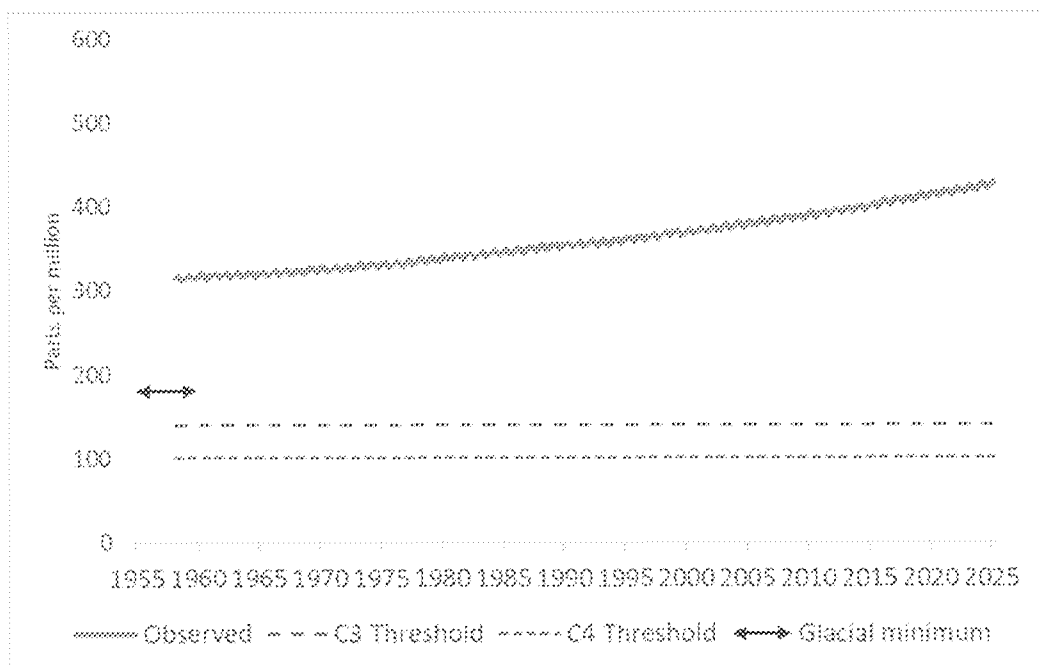


Fig. 3.1.3 CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold (green): Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold (grey): Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum (purple arrow): Minimum level during recent glaciations. CO₂ data source: <https://gml.noaa.gov/ccgg/trends/index.html>

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb "excess" CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend

upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts, they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

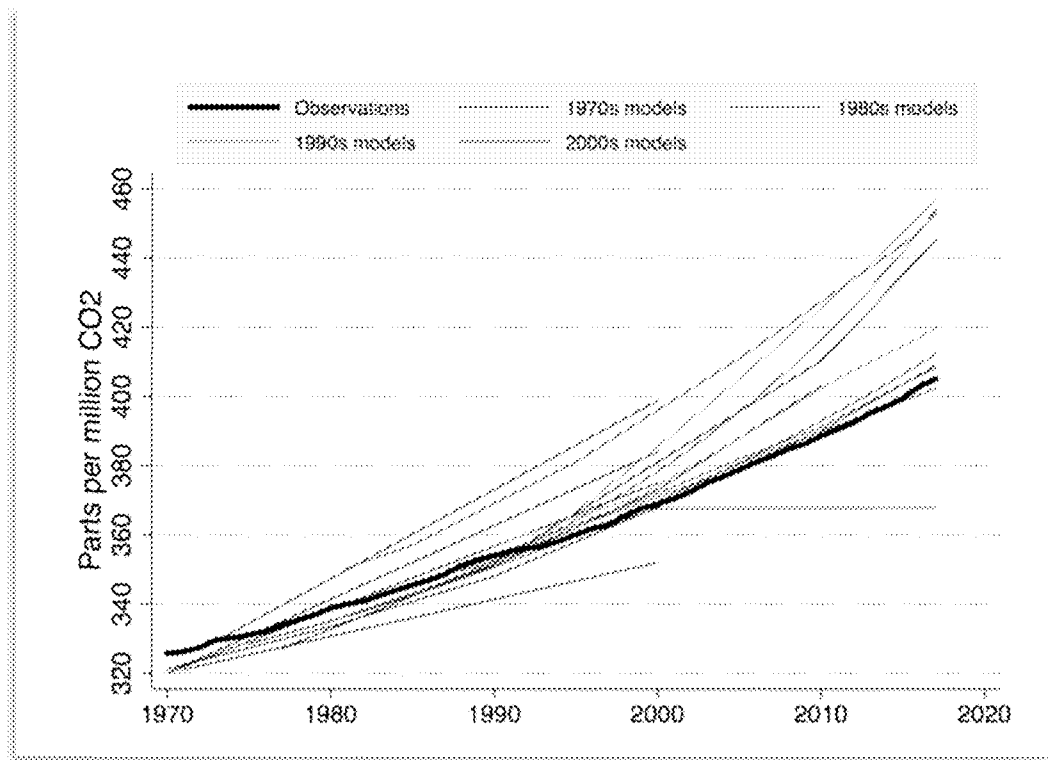


Figure 3.2.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather et al. (2019) Figure S4.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.2.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

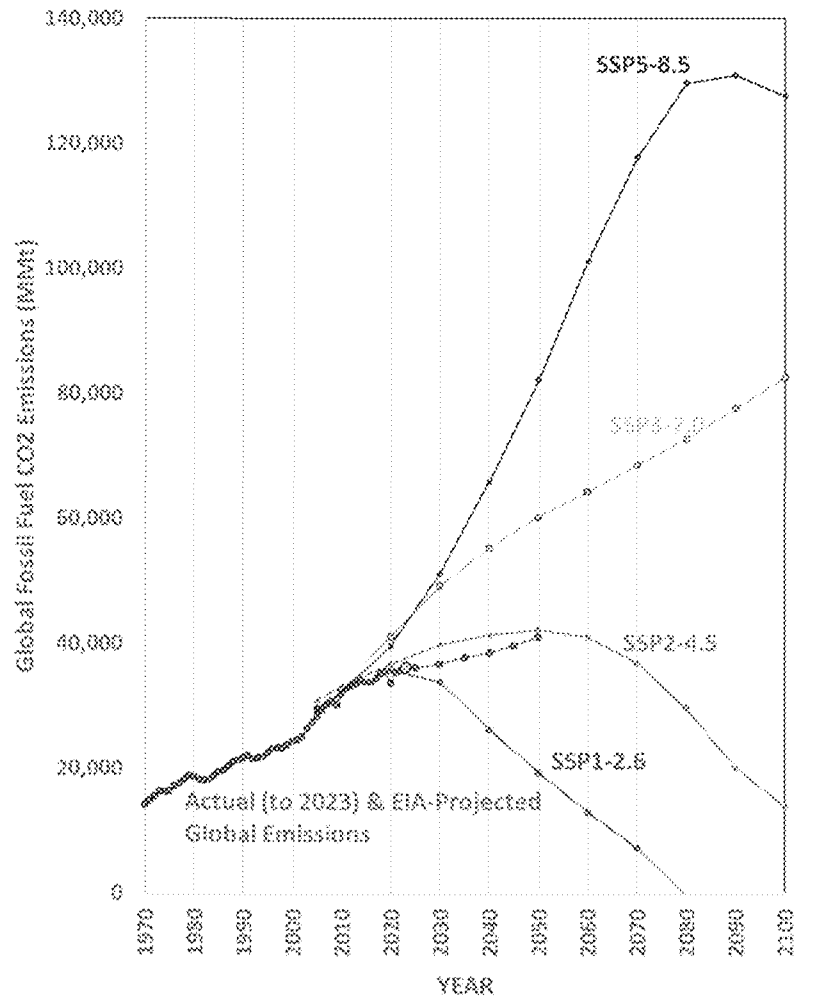


Figure 3.2.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 2.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

{[RM May 18]: Note: moved policy impacts discussion to Ch 13}

Summary

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129, <https://doi.org/10.1029/2024JD041296>

4 Climate Sensitivity to CO₂ Forcing

Chapter Summary

In recent years there has been growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂, owing to poorly resolved processes related to clouds and water vapor. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies. Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is much less plausible. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C with a median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters covering model-observational discrepancies and attribution.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and so also the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney et al. 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed the range with only minor variations until its most recent AR6. AR5 termed 1.5 -- 4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0 - 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based methods of computing climate sensitivity to GHGs

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is typically estimated to be only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 4.1). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by GCMs, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

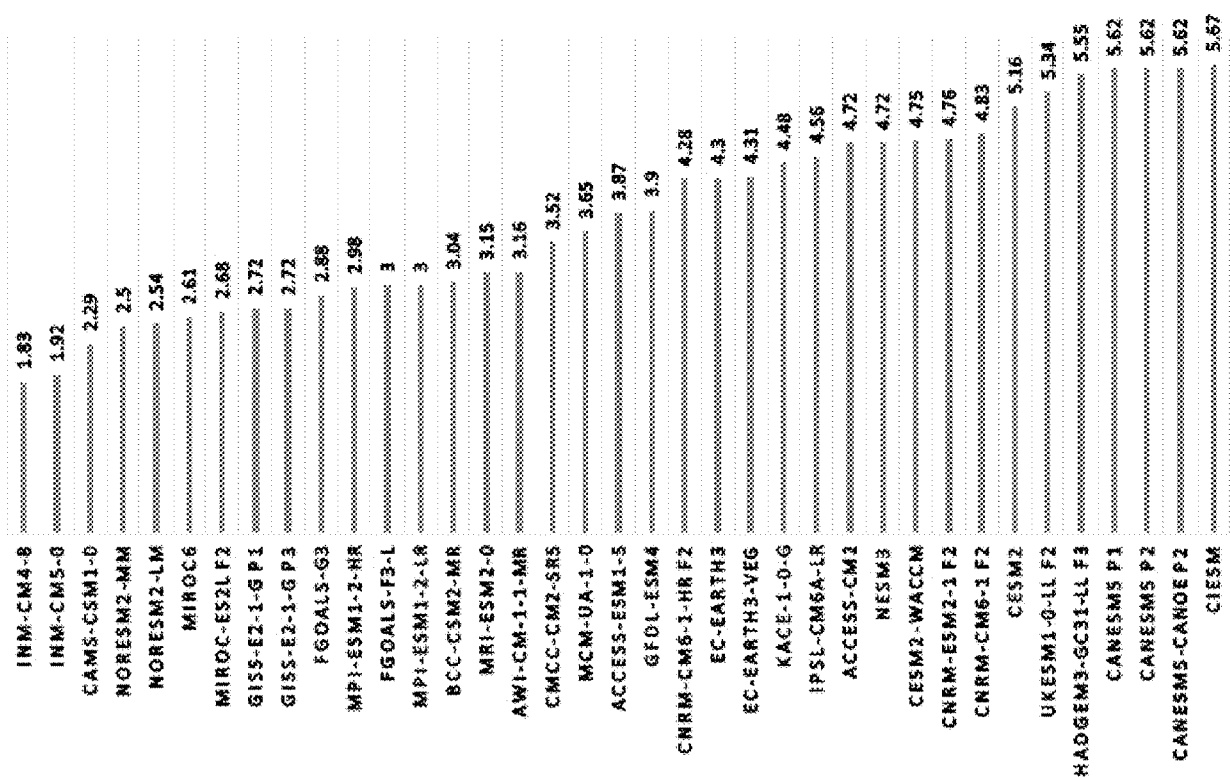


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

4.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects

need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”
Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentration where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is

no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

4.5 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 5, a real-world ECS below the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Chapter 8), where model responses need to be downscaled to align with observed trends.

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems* 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

1. Lan, X., Tans, P. and K.W. Thoning: Trends in globally-averaged CO₂ determined from NOAA Global Monitoring Laboratory measurements. Version Monday, 14-Apr-2025 09:08:57 MDT <https://doi.org/10.15138/9N0H-ZH07>.
2. Zeke Hausfather, "Explainer: How Scientists Estimate Climate Sensitivity," *Carbon Brief*, July 22, 2020, <https://www.carbonbrief.org/explainer-how-scientists-estimate-climate-sensitivity>.
3. Jule Charney et al., "Carbon Dioxide and Climate: A Scientific Assessment," 1979, <https://doi.org/10.17226/12181>.
4. Rajendra K. Pachauri and Leo Meyer, *Climate Change 2014: Synthesis Report* (Geneva, CH: Intergovernmental panel on climate change, 2015).
5. "In-Depth Q&A: The IPCC's Sixth Assessment Report on Climate Science," Carbon Brief, August 9, 2021, <https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-report-on-climate-science>.

6. Nicola Scafetta, “Testing the CMIP6 GCM Simulations versus Surface Temperature Records from 1980–1990 to 2011–2021: High ECS Is Not Supported,” *Climate* 9, no. 11 (2021): 161, <https://doi.org/10.3390/cli9110161>.
7. Brian J. Soden and Isaac M. Held, “An Assessment of Climate Feedbacks in Coupled Ocean–Atmosphere Models,” *Journal of Climate* 19, no. 14 (July 15, 2006): 3354–3360, <https://doi.org/10.1175/jcli3799.1>.
8. S. C. Sherwood et al., “An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence,” *Reviews of Geophysics* 58, no. 4 (July 22, 2020), <https://doi.org/10.1029/2019rg000678>.
9. Judith A. Curry and Peter J. Webster, “Thermodynamic Feedbacks in the Climate System,” in *Thermodynamics of Atmospheres and Oceans* (New York, NY: Academic Press, 1999), 351–385.
10. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
11. D. Chen et al., “Framing, Context, and Methods.”
12. Mark D. Zelinka et al., “Causes of Higher Climate Sensitivity in CMIP6 Models,” *Geophysical Research Letters* 47, no. 1 (2020): e2019GL085782, <https://doi.org/10.1029/2019GL085782>.
13. Thorsten Mauritsen and Johann Jungclaus, “Tuning the MPI-ESM1.2 Global Climate Model to Improve the Match With Instrumental Record Warming by Lowering Its Climate Sensitivity,” *Journal of Advances in Modeling Earth Systems* 12, no. 7 (2020): e2019MS002037, <https://doi.org/10.1029/2019MS002037>.
14. Alexander Otto et al., “Energy Budget Constraints on Climate Response,” *Nature Geoscience* 6, no. 6 (May 19, 2013): 415–416, <https://doi.org/10.1038/ngeo1836>.
15. Steven C. Sherwood and Chris E. Forest, “Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?” *Atmospheric Chemistry and Physics* 24, no. 5 (2024): 2679–2686, <https://doi.org/10.5194/acp-24-2679-2024>.
16. “Why Low-End 'Climate Sensitivity' Can Now Be Ruled Out,” Carbon Brief, July 22, 2020, <https://www.carbonbrief.org/guest-post-why-low-end-climate-sensitivity-can-now-be-ruled-out>.
17. S. C. Sherwood et al., “An Assessment of Earth's Climate Sensitivity.”
18. D. Chen et al., “Framing, Context, and Methods.”
19. Nicholas Lewis, “Objectively Combining Climate Sensitivity Evidence,” *Climate Dynamics* 61, no. 9–10 (2023): 3155–3163, <https://doi.org/10.1007/s00382-022-06398-8>.
20. Ibid.
21. Steven C. Sherwood and Chris E. Forest, “Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?”
22. Nicholas Lewis, “Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024),” *EGUsphere* [preprint], 2025, <https://doi.org/10.5194/egusphere-2025-1179>.
23. P. Forster et al., (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V. et al. (eds.)], Cambridge University Press, 2021.
24. Richard Seager et al., “Strengthening Tropical Pacific Zonal Sea Surface Temperature Gradient Consistent with Rising Greenhouse Gases,” *Nature Climate Change* 9, no. 7 (2019): 517–522, <https://doi.org/10.1038/s41558-019-0505-x>.

25. Sangyeop Lee et al., "Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint," *Climate Dynamics* 62, no. 1–2 (2024): 229–246, <https://doi.org/10.1007/s00382-023-06741-7>.
26. D. Chen et al., "Framing, Context, and Methods."
27. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
28. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
29. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
30. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)."

Nierenberg, William et al. (1983) *Changing Climate: Report of the Carbon Dioxide Assessment Committee*. Washington, National Academies Press 1983.

5 Models versus Observations in the Recent Past

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past few decades. In response to observed changes in forcing inputs they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

They also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The IPCC has acknowledged some of these issues, buried the amplification problem and ignored others.

The warm bias discussed here is consistent with independent evidence of model bias presented in Chapters 4 (measuring climate sensitivity) and 8 (optimal fingerprinting). Given the persistent warm bias in so many key aspects of climate model performance, users are justified in assuming that projections of future warming are also very likely to be biased too warm.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide the theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. In order to determine the value of climate models for this purpose, it is reasonable to ask how well they have reproduced climate variations over the recent past, say the last half-century.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

5.2 Surface warming

A straightforward test of climate model validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 6.1 is reproduced from Scaffeta (2023), a peer-reviewed 2023 study which groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

Columns correspond to model groups showing low-ECS to high-ECS. Rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one

standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

Examination of the leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

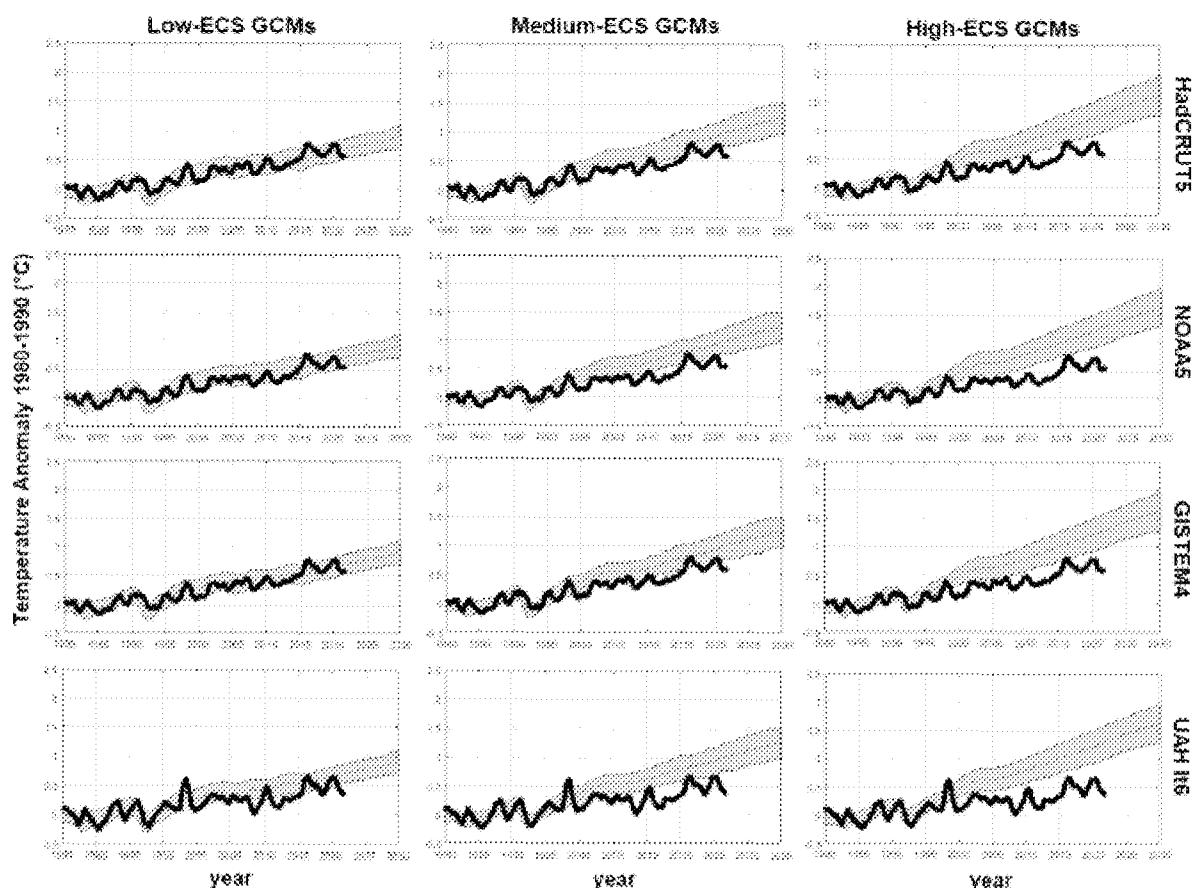
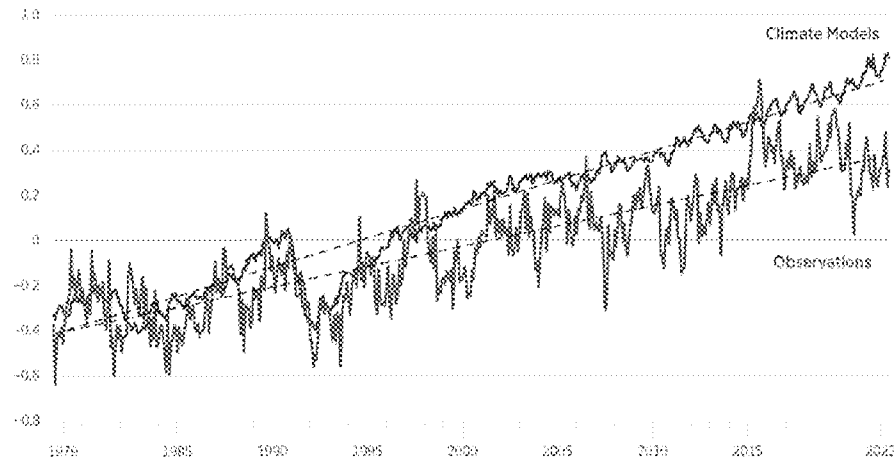


Figure 5.1: model-observational comparisons for Earth’s surface warming. Source: Scafetta N. Climate Dynamics 2023 Fig.2. Rows: temperature data products as indicated. Columns: Low- to High-ECS models. Observations: black line. Model simulations: yellow band.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by focusing on average surface temperature data products versus the average climate model warming, summarized in Figure 6.2.

Global Average Surface-Air Temperature Variations, 1979~2022

DEPARTURE FROM 1951-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Authors' calculations based on data from five different observation-based datasets and 35 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and KNMI Climate Explorer, "Starting Point," <https://climate.knmi.nl/Start.asp> (accessed January 10, 2024).

Figure 5.2: Models versus observations at the surface. Source: Spencer (2024)

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the troposphere over the tropics. Since this region generates the bulk of atmospheric warming in a GCM it is important to get the trends right. The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time not better, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 5.3). Every single model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 5.4).

In most individual cases the bias is statistically significant and on average it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If a group of models were to appear that had a realistic representation of global tropospheric warming, it would likely have to have a lower ECS than even the low-ECS members of the CMIP6 ensemble

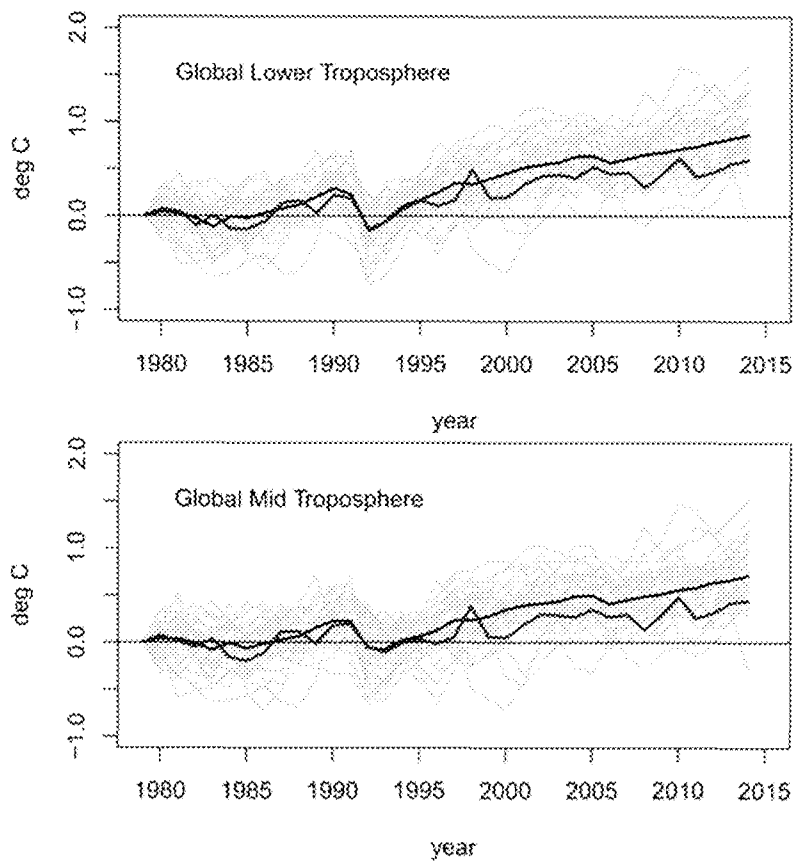


Figure 5.3: Models versus observations in the global troposphere. Source: McKittrick and Christy (2020). Gray lines: model runs. Black: average model run. Blue: average of satellite, radiosonde and reanalysis observations.

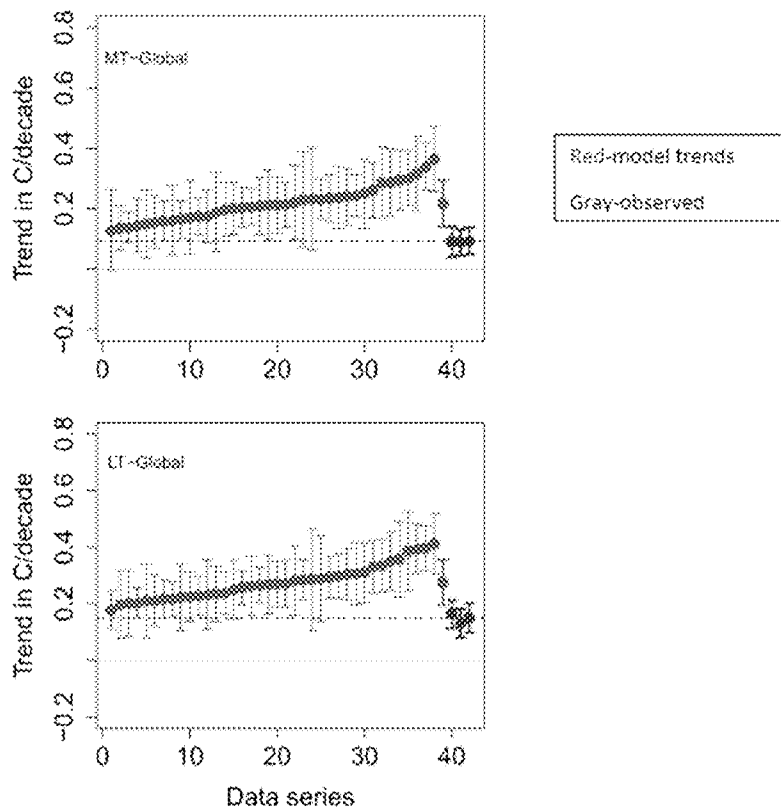
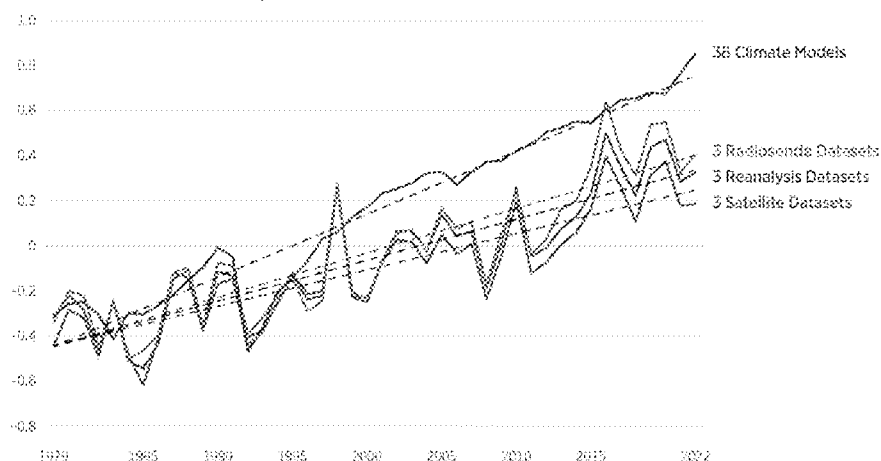


Figure 5.4: Modeled versus observed warming trends in the global troposphere. Adapted from McKittrick and Christy (2020). Red dots: model warming trend in °C/decade with 95% confidence interval bars. Gray dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars.

Spencer (2024) shows the mismatch is also present in the lower troposphere:

Global Lower Atmospheric Temperature Variations, 1979-2022

DEPARTURE FROM 1991-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES:

- Author's calculations based on data from Ross McKittrick and John Christy, "Persistent Warming Bias in CMIP6 Tropospheric Layers," *Earth and Space Science*, Vol. 7, No. 11 (Nov 14, 2020), <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020EF000128> (accessed January 10, 2023).
- Author's calculations based on data from American Meteorological Society, *State of the Climate in 2022*, <https://www.wamweather.gov/index.cfm/analysis/outlook/bulletin-of-the-american-meteorological-society-bulletin-of-the-climate/> (accessed January 9, 2023).

BG3809 heritage.org

Figure 5.5: Comparison of average trends in lower troposphere, 1979-2022. Source: Spencer (2024).

As mentioned the IPCC has long acknowledged the model-observational mismatch. The AR6 pp. 443-444 confirms model-observational mismatch in the troposphere the tropics (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5

and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

It is worth noting that despite the enormous accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias. In other contexts they declare *high confidence* in phenomena established with much less evidence.

5.4 Vertical profile mismatch and excess amplification

An important element of the model-observational discrepancy is the excess amplification with altitude found in climate models. A comparison was shown in the IPCC AR5 Chapter 10, although only in the online supplement. The diagram, reproduced below as Figure 5.6, compares temperature trends by altitude between models and observations, divided up into latitude bands.

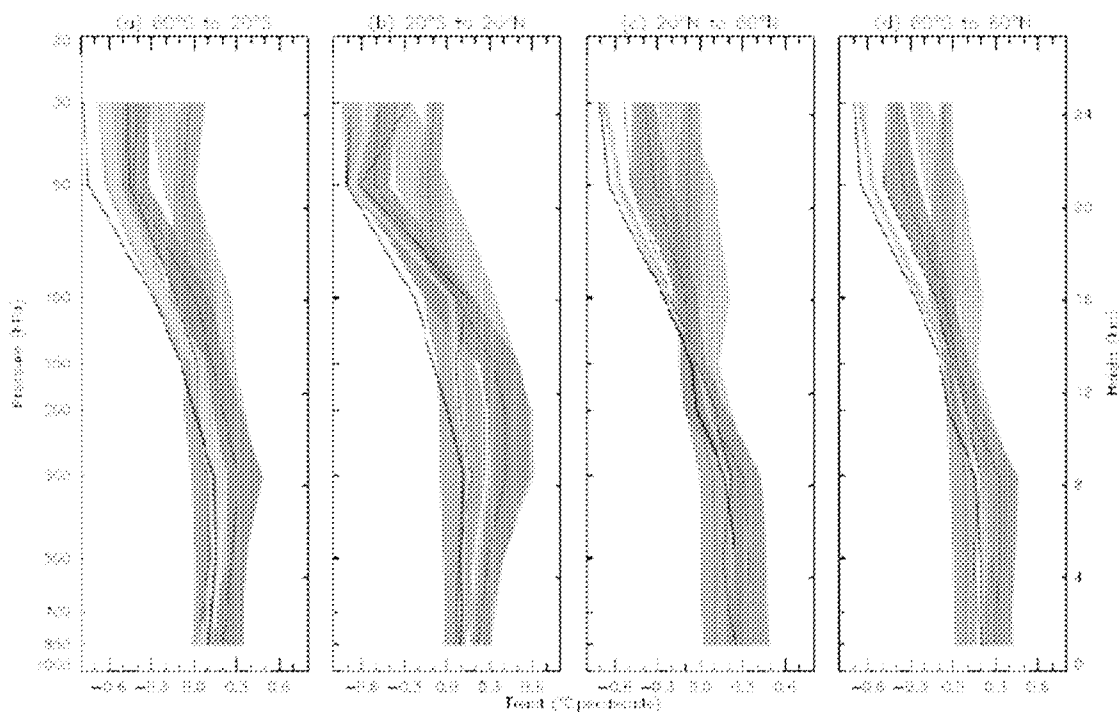


Figure 10.SM.1 | Observed and simulated zonal mean temperature trends from 1979 to 2011 for CMIP5 simulations containing both anthropogenic and natural forcings (red), natural forcings only (blue) and greenhouse gas forcings only (green), where the 25th to 75th percentile ranges of the ensembles are shown. Three radiosonde observations are shown (thick black line: Hadley Centre Atmospheric Temperature data set 2 (HadAT2), thin black line: Radiosonde Observation (Reanalysis (RACMO)) 1.5, dark grey line: Radiosonde Observation Composite (RACMO-com), 1.5 ensemble and light grey: RACMO-com 1.5 ensemble. (adapted from Watt et al. [2013] but for the more recent period from 1979 to 2014.)

10.SM.6

Figure 5.6: Vertical warming pattern by latitude band. Source: IPCC AR5 Figure 10.SM.1

The Figure is not referenced in the main report nor in any summary. What it shows, although it is not apparent at first glance, is that the 1979-2010 warming in the lower troposphere is so minimal it is consistent with models having no GHG forcing in them at all, and is inconsistent with the model runs that do have GHG forcing. Here is the main global band (60S to 60N) expanded with the observed trends highlighted in yellow:

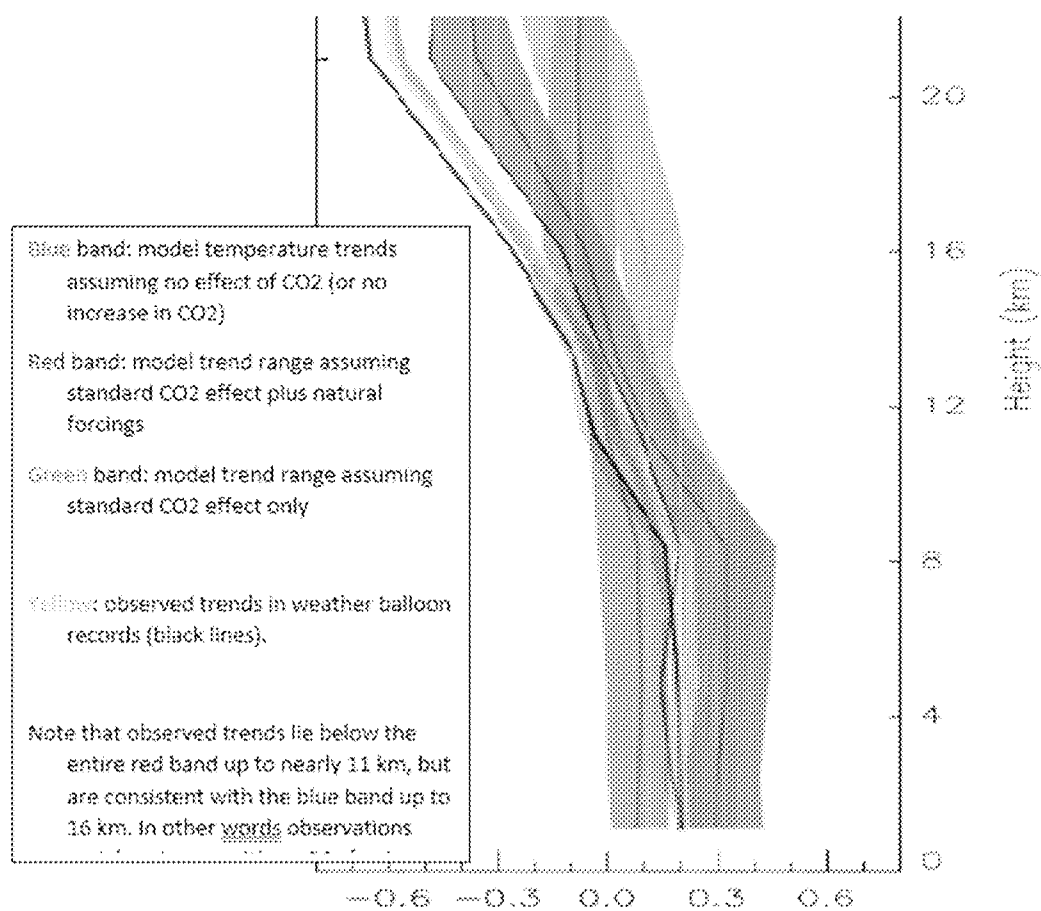


Figure 5.7: Adapted from IPCC AR5 Figure 10.SM.1

The next version of the Figure draws further detail out of the tropics band:

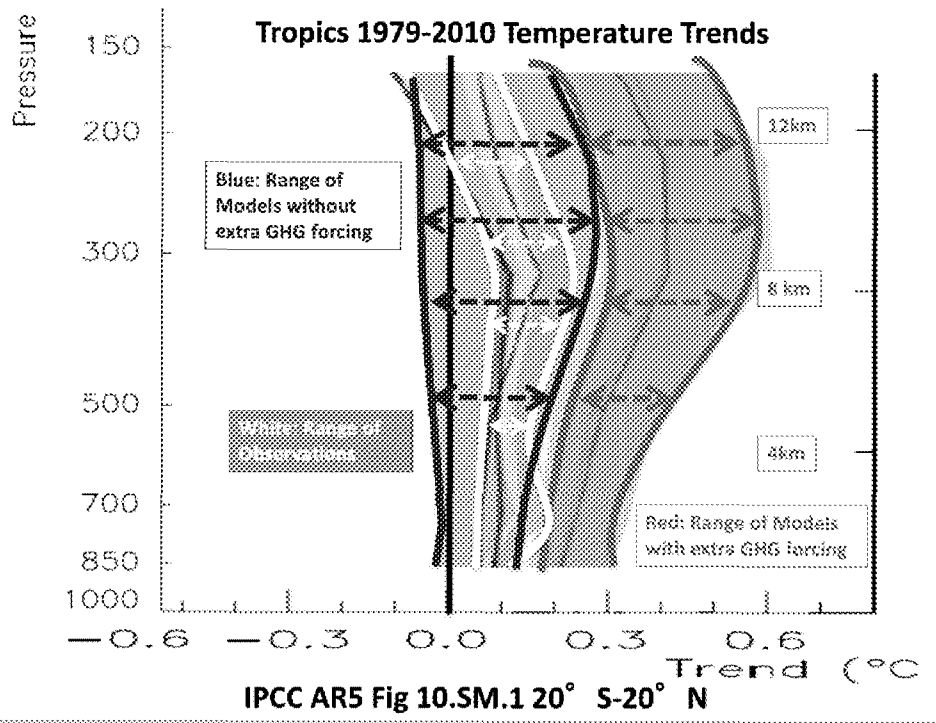


Figure 5.8: Adapted from IPCC AR5 Figure 10.SM.1.

In the tropics, where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.9. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.9 is the TTT layer average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

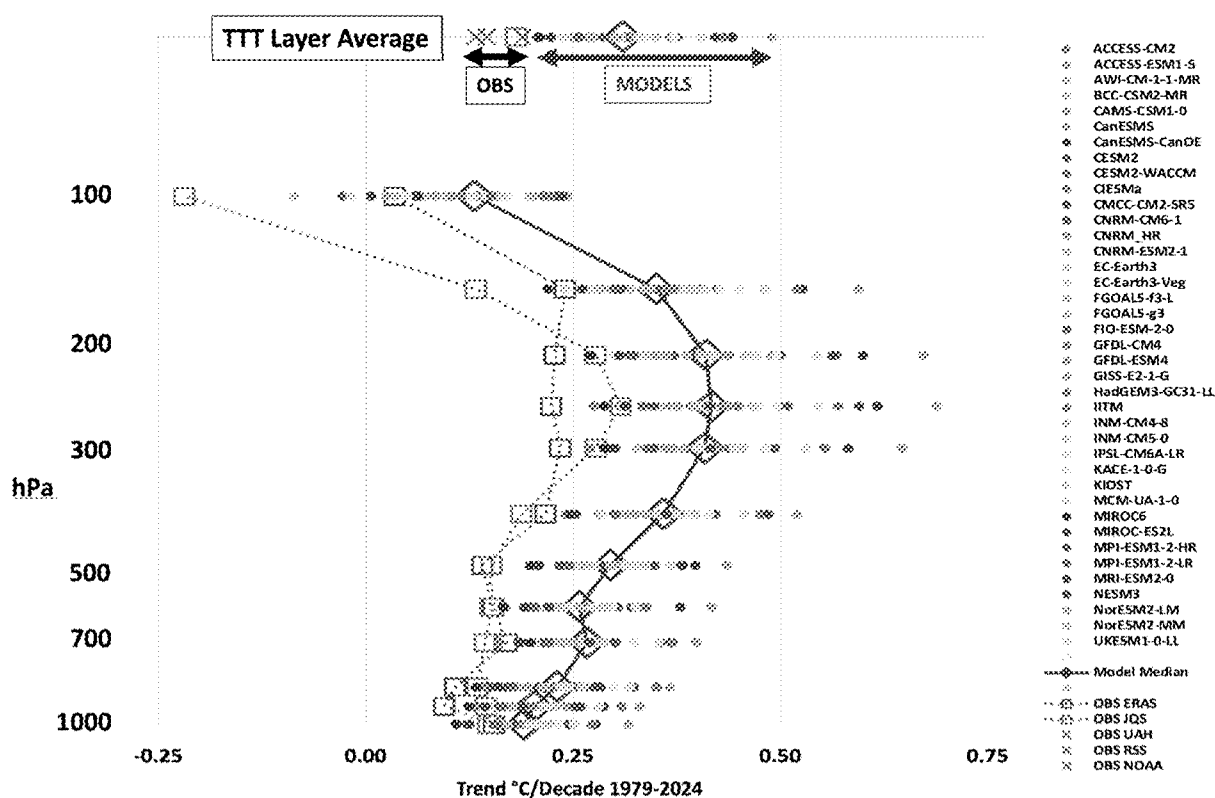


Figure 5.9: Modeled versus observed warming, tropical troposphere. Source: Christy and McNider (2017).

Some defenders of the models have argued that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), which was not discussed in the AR6, showed that models project greater amplification with altitude than is observed. That paper gave rise to an online debate over whether the amplification rates were being correctly calculated, and whether the discrepancy between models and observations was statistically significant. The topic involves very advanced statistical theory and was dealt with by two experts in time series analysis (Vogelsang and Nawaz 2016) who found that Klotzbach’s conclusions were valid, and that observed amplification is significantly smaller than the model-projected rates. The IPCC AR6 made no mention of this work either.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.”

5.6 Water vapour trends mismatch

Much of the warming in climate models derives not from GHG increases themselves but from water vapour feedbacks: extra warming induced by the projected accumulation of water vapour in the atmosphere after it warms due to CO₂. But new evidence (Simpson et al. 2024) shows that models have over-projected increases in humidity.

“Water vapor in the atmosphere is expected to rise with warming because a warmer atmosphere can hold more moisture. However, over the last four decades, near-surface water vapor has not increased over arid and semi-arid regions. This is contrary to all climate model simulations in which it rises at a rate close to theoretical expectations, even over dry regions. This may indicate a major model misrepresentation of hydroclimate-related processes; models increase water vapor to satisfy the increased atmospheric demand, while this has not happened in reality.”
(Simpson et al. 2024)

While the models and observations matched over the 1988 to 2006 interval they diverge after that, directly contradicting model projections.

5.7 Snow cover mismatch

According to the Rutgers University Snow Lab (undated) the Northern Hemisphere winter snow cover shows an increasing trend over time.

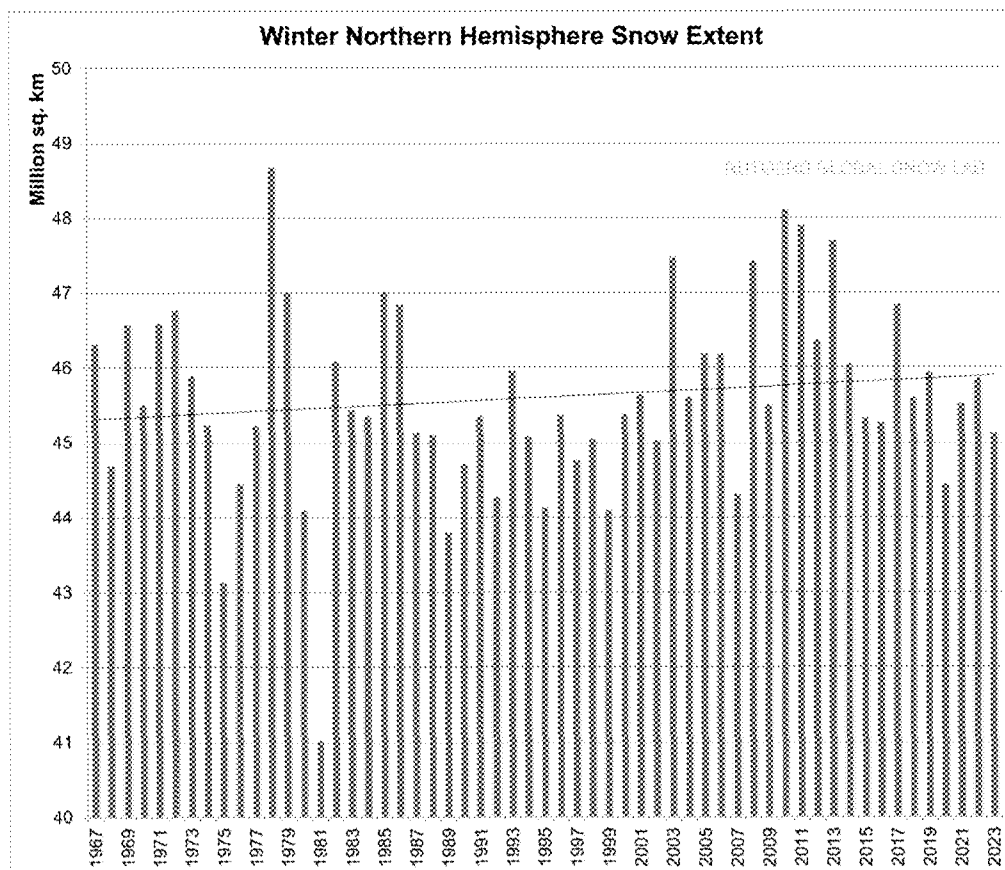


Figure 5.10: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (February 24, 2024)

Models project declining Northern Hemisphere snow cover due to climate warming. But observations do not support this, as explained by Connolly et al. (2019).

Observed changes in Northern Hemisphere snow cover from satellite records were compared to those predicted by all available Coupled Model Intercomparison Project Phase 5 (“CMIP5”) climate models over the duration of the satellite’s records, i.e., 1967–2018. A total of 196 climate model runs were analyzed (taken from 24 climate models). Separate analyses were conducted for the annual averages and for each of the seasons (winter, spring, summer, and autumn/fall). A longer record (1922–2018) for the spring season which combines ground-based measurements with satellite measurements was also compared to the model outputs. **The climate models were found to poorly explain the observed trends. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions.** Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant. Connolly et al. (2019), emphasis added.

5.8 US Corn Belt

One of the largest discrepancies between models and observations can be found when we test them in a region of particular importance to global food production: the U.S. Corn Belt. Fig. 6.11 shows the warming trends for summertime (June, July, August) for the U.S. 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) produced too much warming compared to observations (blue) during 1973 to 2022.

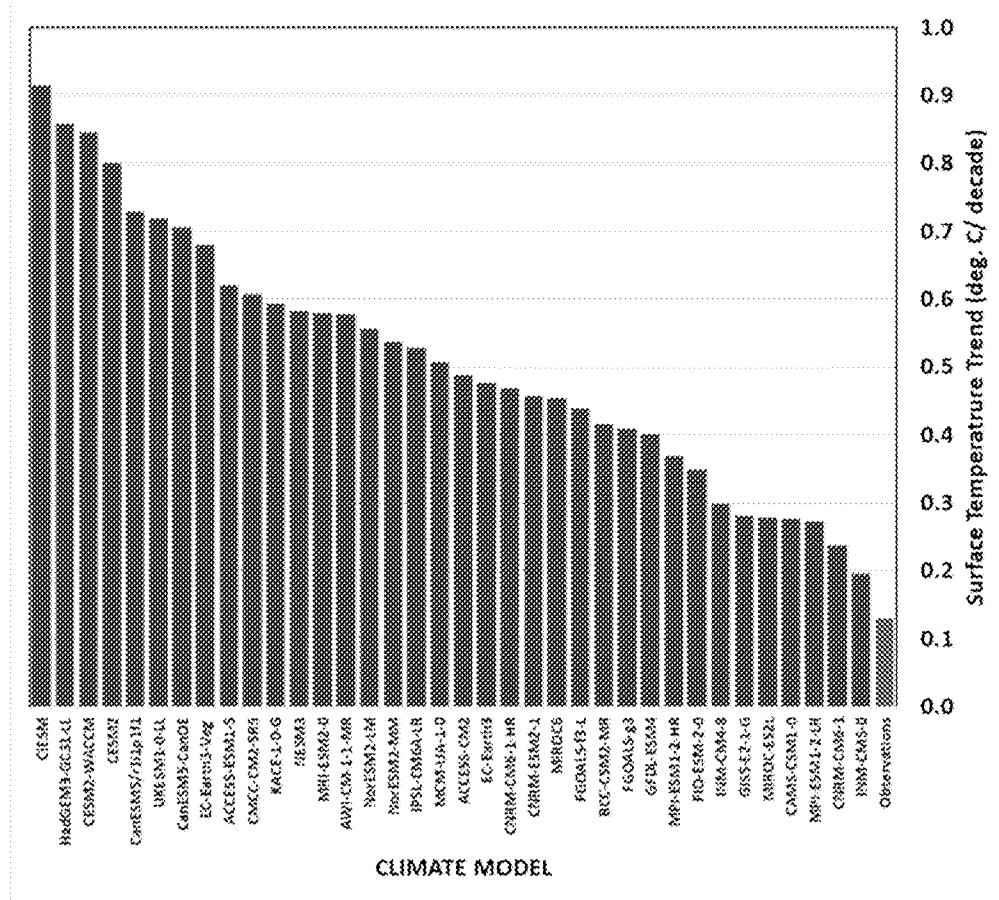


Figure 5.11: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 9, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, which is in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

6 Extreme weather

Chapter Summary

Contrary to popular belief and frequent claims by the media and many political leaders, most types of extreme weather exhibit no statistically significant trends, nor do assessment reports of the IPCC or the NCA claim to have detected them. There has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, but numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term trends are not detectable. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfire activity has increased in the US in recent decades but has declined globally, and US wildfire activity is down significantly relative to the early 20th century. It is also low compared to the estimated natural baseline level. Changes in US wildfire activity are strongly affected by changing forest fire management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. First, “climate” refers to the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics¹ (see *Perils of short data records* below). As will be discussed in Chapter 8, making attributions of cause for extreme events that occur only once in a record requires heroic assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate the full extent of natural variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is not present in a given century-long record.

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 6.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

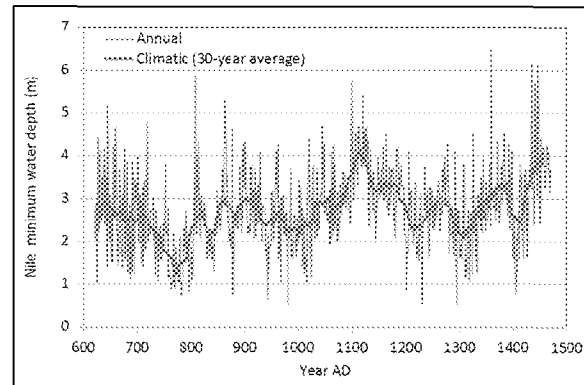


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from (Koutsoyiannis 2013)

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I.

NCA23: The US *Climate Science Special Report of the Fifth National Climate Assessment* (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis is added.

6.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 8 looks at causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 33 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 25 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

6.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)³

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

Global Major Hurricane Frequency -- 12 month running sums -- @RyanMaue

Updated March 10, 2025

Last 30-years, annual: 45 H | 24 M

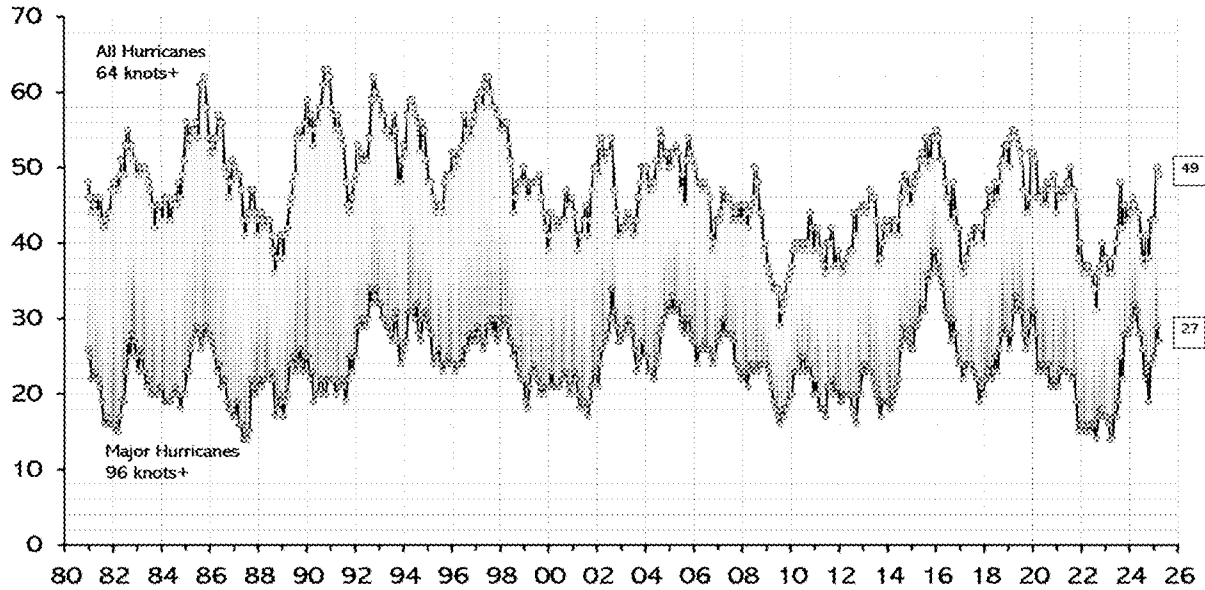


Figure 6.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35 percent of total global hurricanes whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 6.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

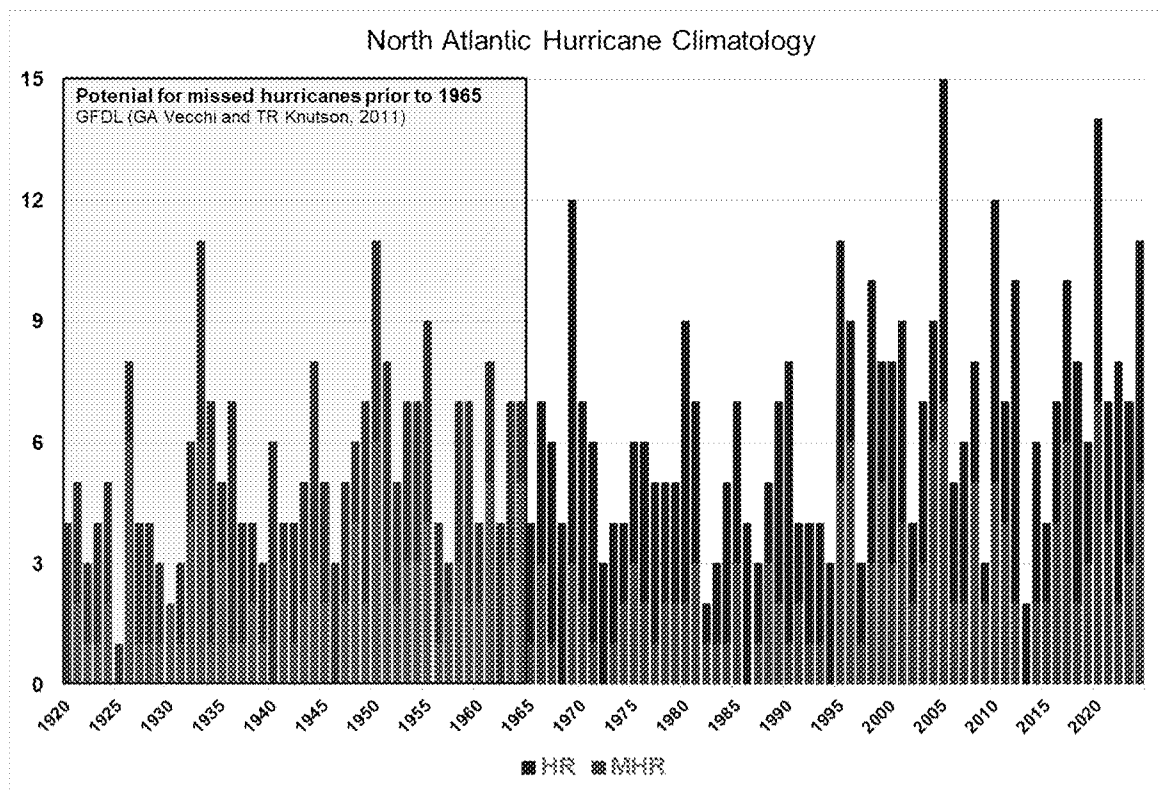


Figure 6.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 6.3.2 that Atlantic hurricanes show strong variations on decadal and multidecadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 6.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

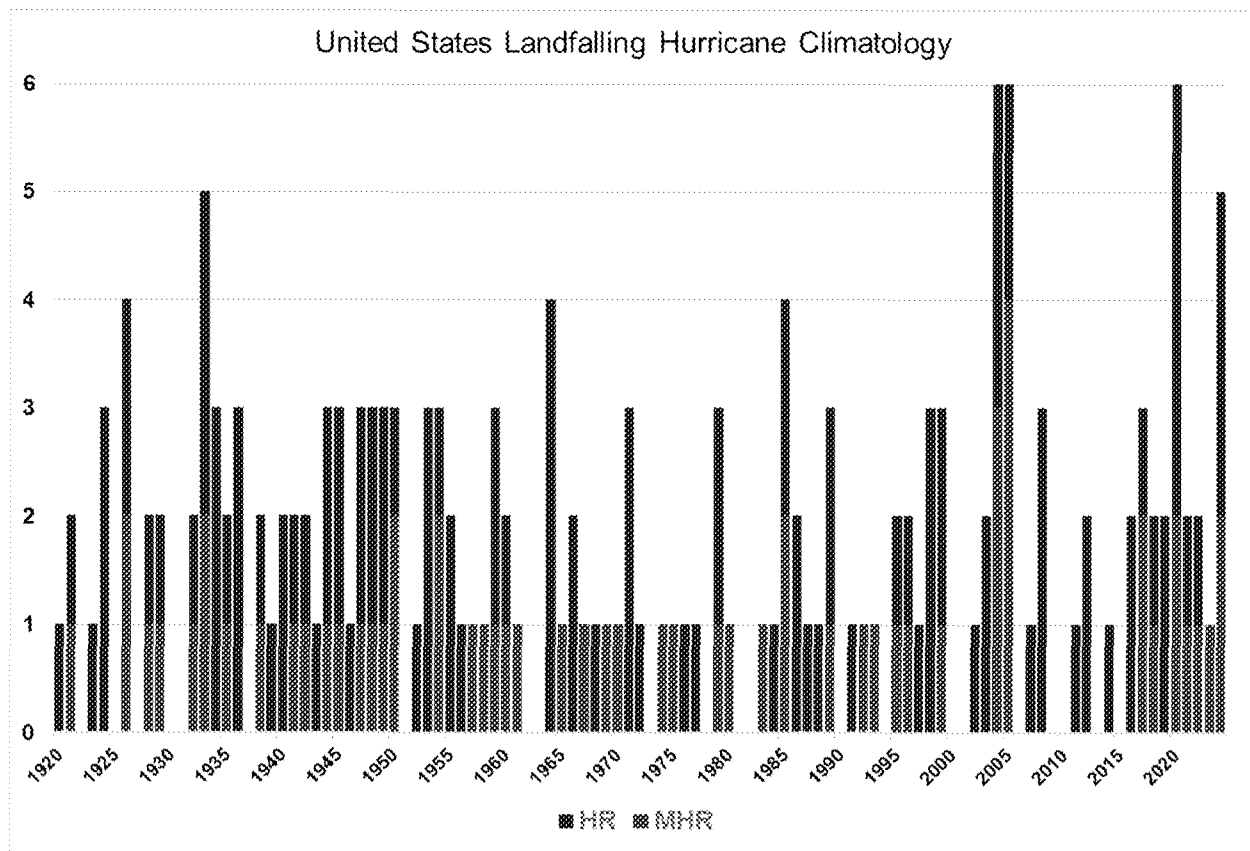


Figure 6.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 6.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 6.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 6.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew

4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

6.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: "Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C])." (pp. 190-191)

NCA17: "Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s.**" (pp. 190-191)

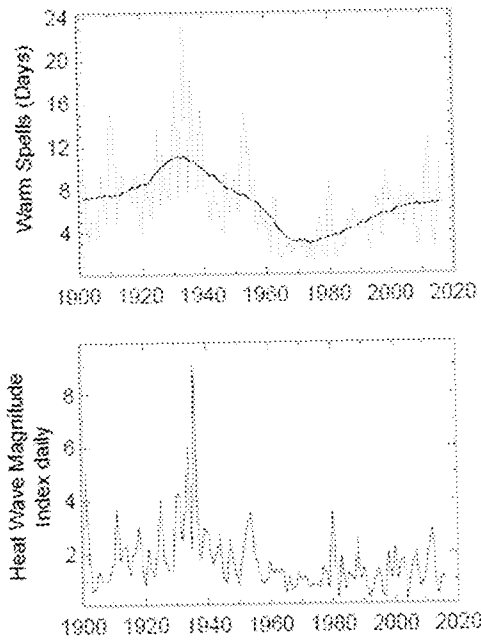


Figure 6.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

6.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

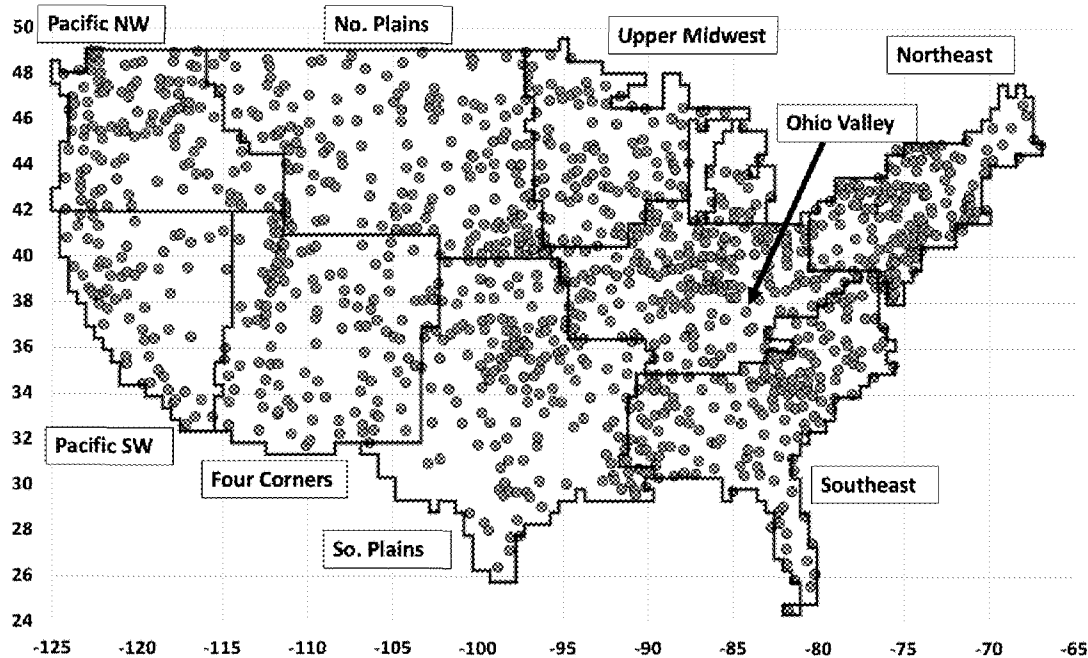


Figure 6.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 6.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

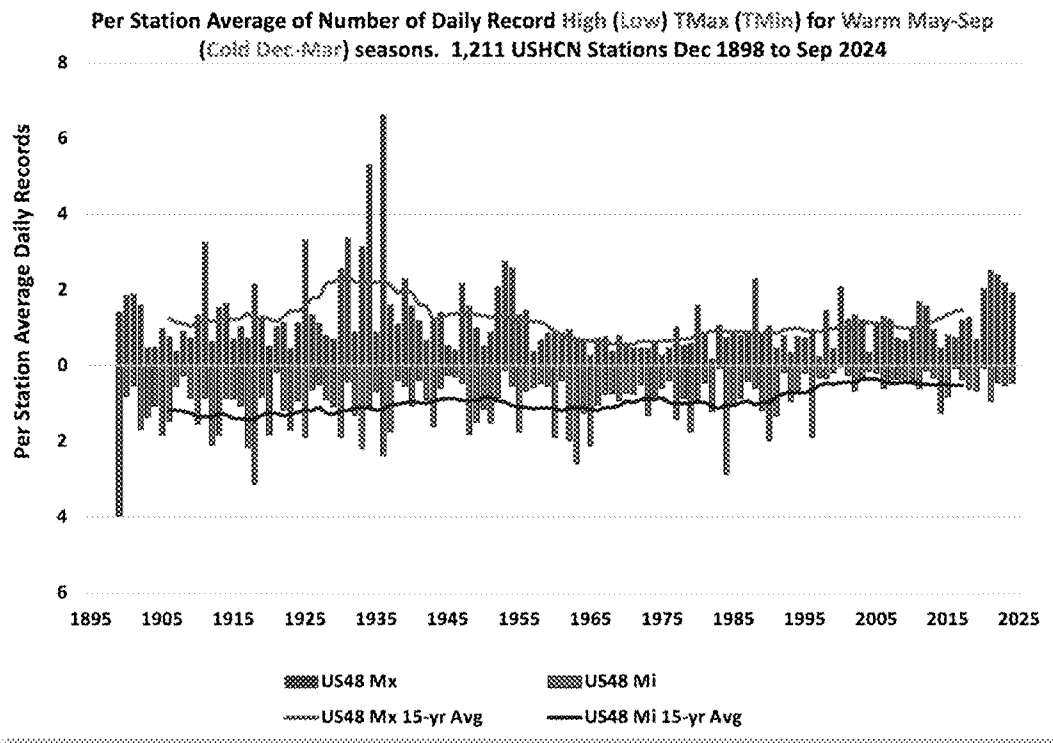


Figure 6.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

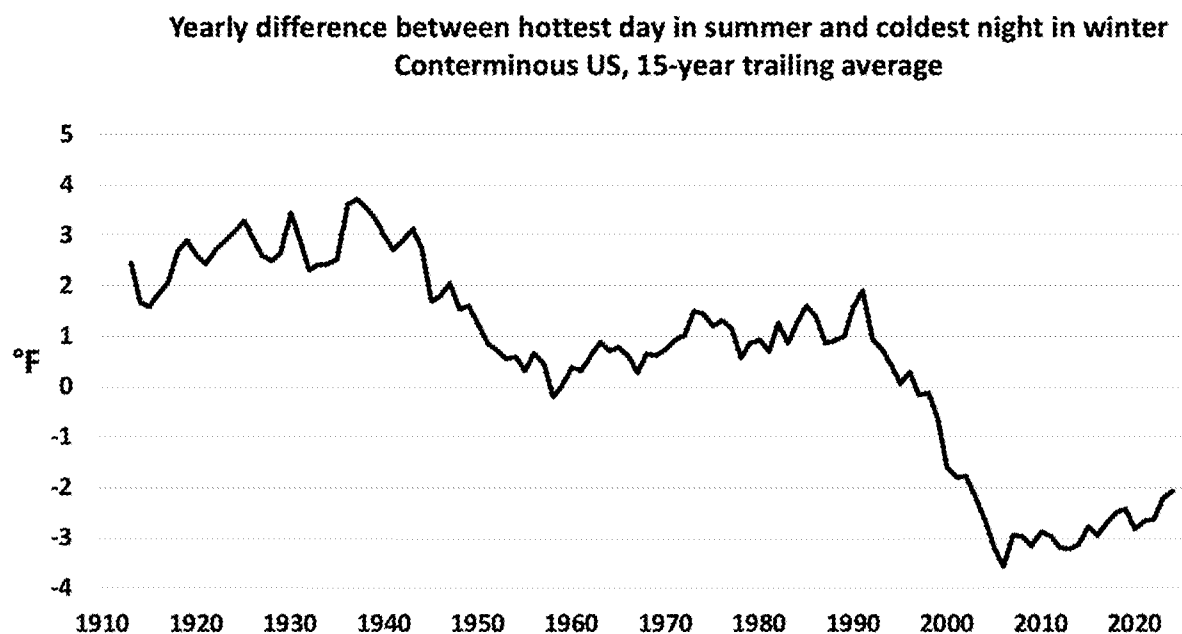


Figure 6.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

6.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

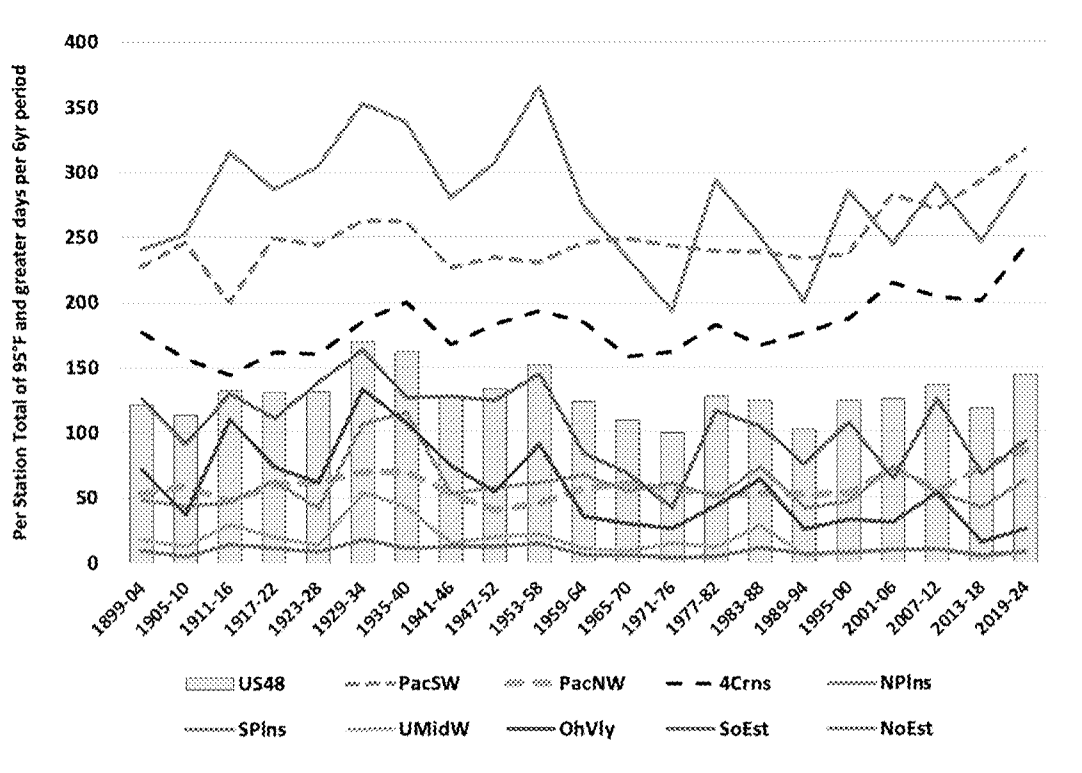


Figure 6.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced in the NCA23, an event we examine more closely in Section 8.4. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” WHERE IS THIS HEADING FROM – Perhaps NCA23? suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the figures above.

6.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

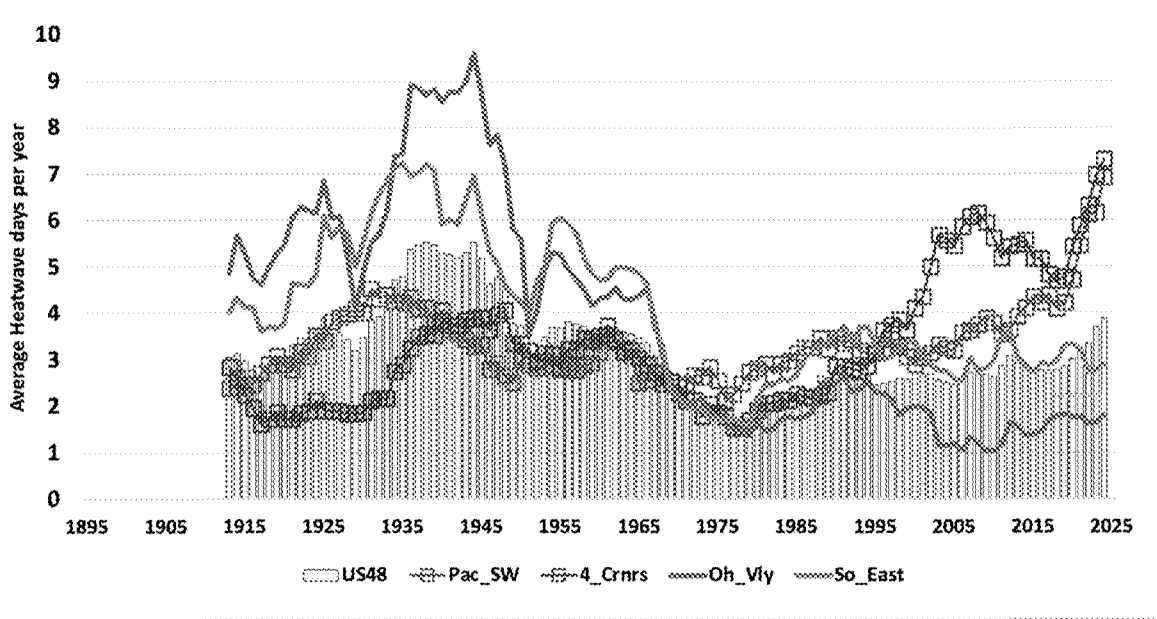


Figure 6.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ, NM, UT, CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 6.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

6.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

6.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

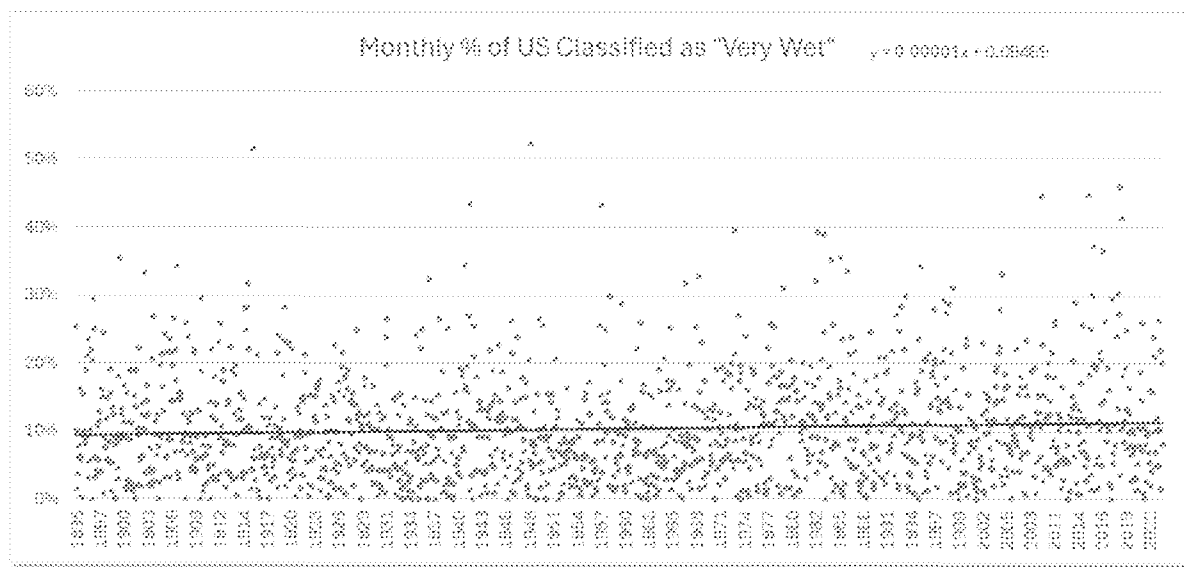


Figure 6.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 6.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 6.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, in a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 6.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While

erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

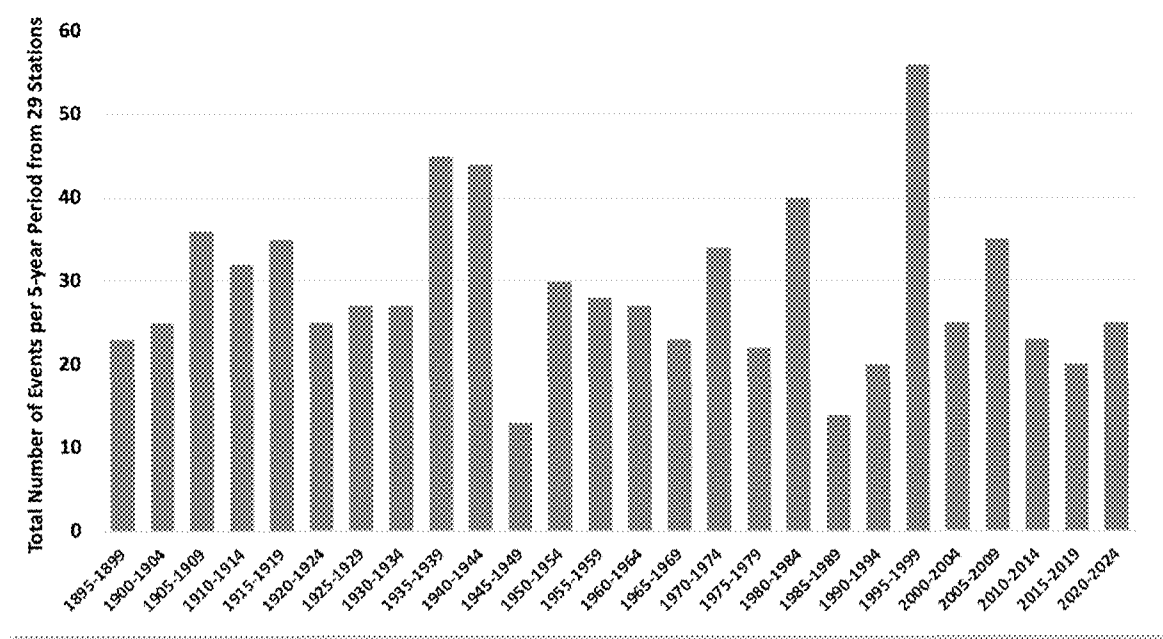


Figure 6.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

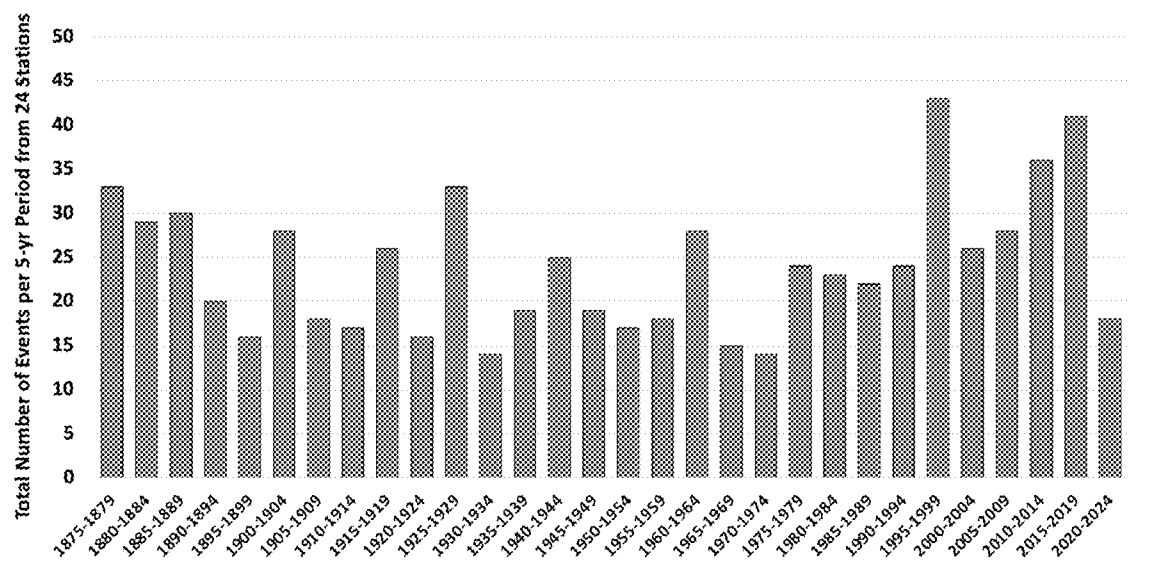


Figure 6.5.4. As in Fig. 6.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME; insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 6.5.5 shows the same calculation for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it shall be examined more closely.

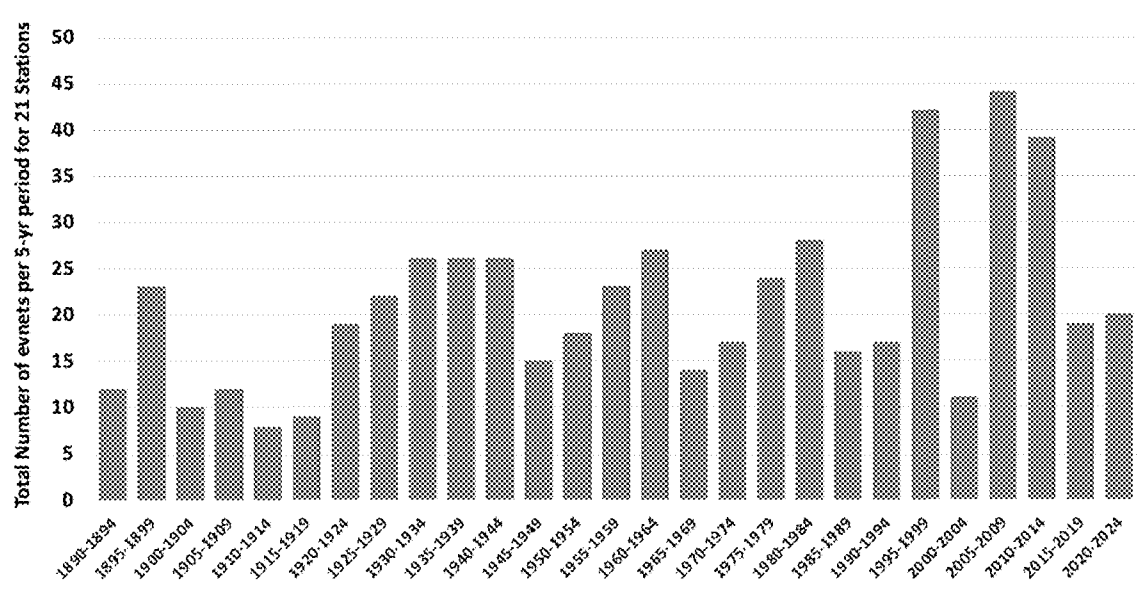


Figure 6.5.5. As in Fig. 7.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 21 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 6.5.5 that includes PA and NJ and reported differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes. They reported a dramatic increase (317%) in 24-hr events exceeding 6 inches. Using the information in Fig. 6.5.5 over the same years we find a 51% increase in the frequency of heavy events. However the frequency drops sharply after 2014, returning to the long-term average over the next decade. It was thus unfortunate that Howarth et al. sample ended in 2014.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.5.5 and 6.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, the pattern was not region-wide nor did the change persist after 2014.

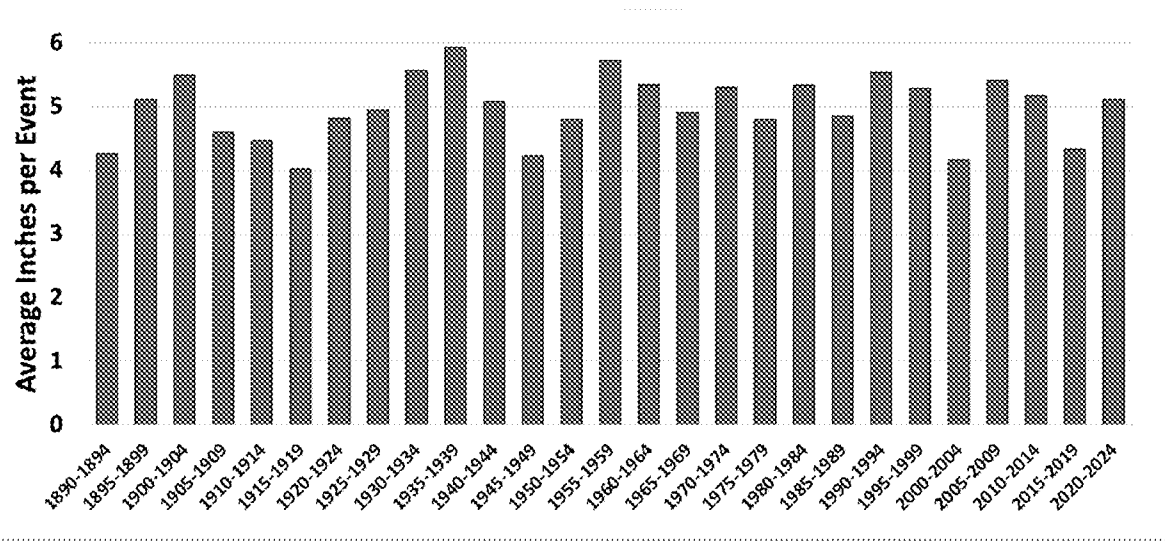


Figure 6.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.5.5.

In summary, while apparent increases in extreme precipitation events in some regions over short intervals can be found in the record, the evidence from long term, nationwide historical records does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

6.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

6.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 6.8.1, US long term data shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

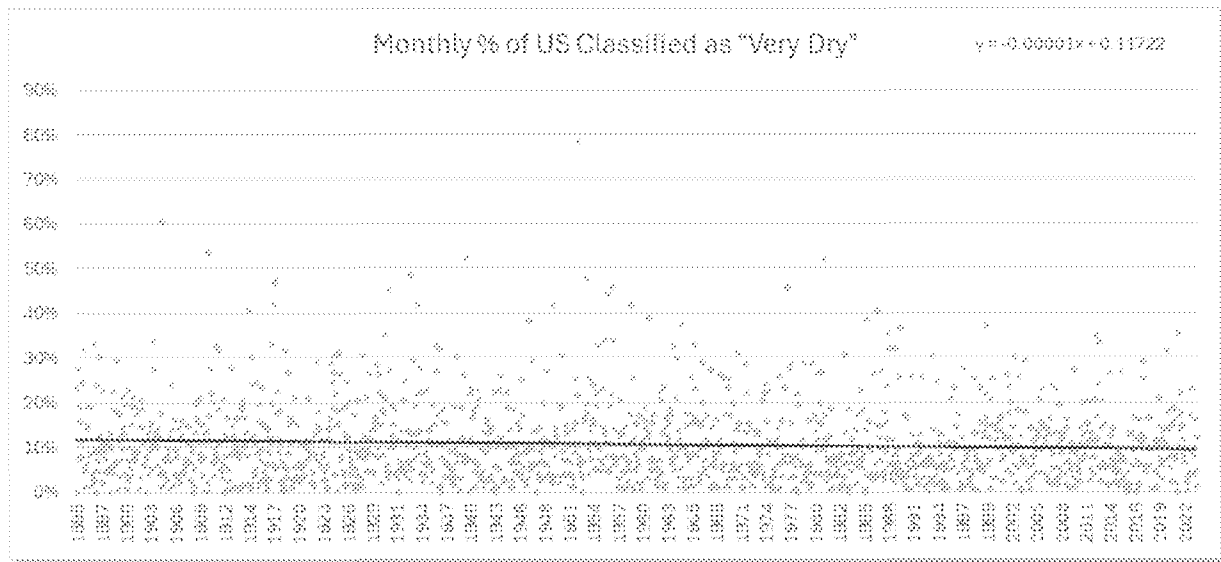


Figure 6.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: "it is possible to state firmly that global and main grain countries' drought area and intensity trends have not been following global climate warming since 1980's."

6.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 6.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.9.2.

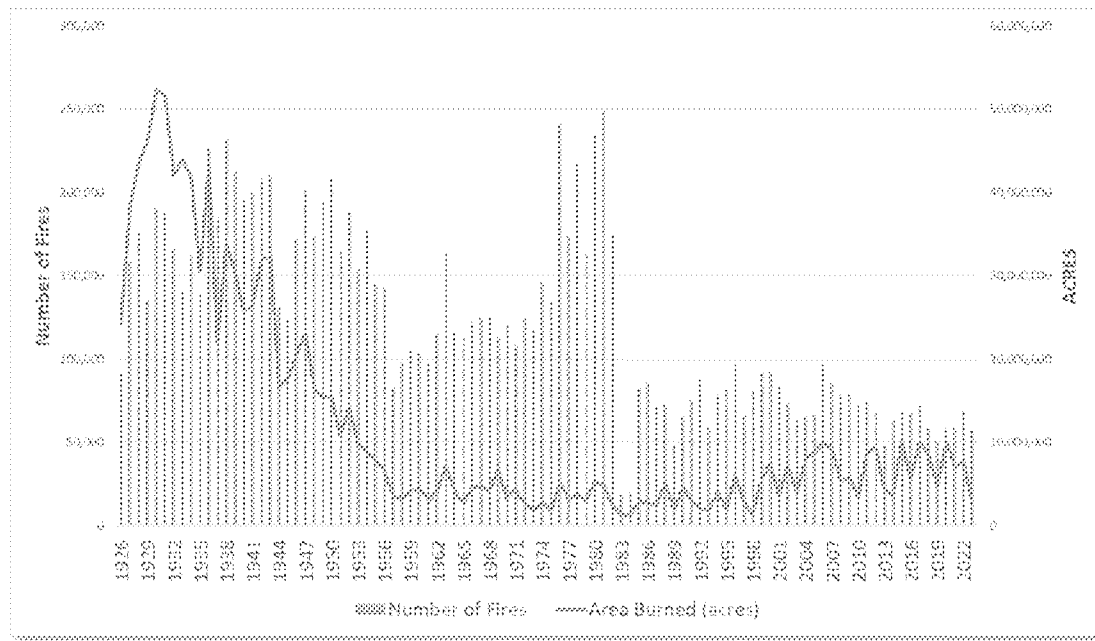


Figure 6.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Centre data Pre-2017 webarchive.org.

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and

controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

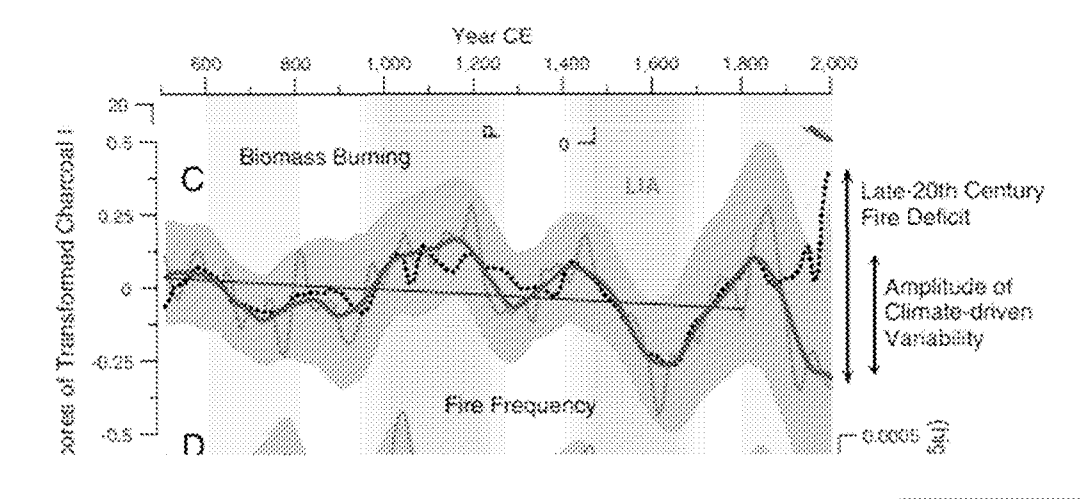


Figure 6.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

References

Brewer, W., *Up and Down California in 1860–1864 The Journal of William H. Brewer* (Berkley, CA: University of California Press, 1930).

Christy, J.R. W. Norris and R.T. McNider, 2009. Surface temperature variations in East Africa and possible causes. *J. Climate*, 22, 3342–3356. DOI: 10.1175/2008JCLI2726.1.

Cohn, Timothy A., Lins, Harry F. (2005). Nature's style: naturally trendy. *Geophys. Res. Lett.* 32. <https://doi.org/10.1029/2005GL024476>.

Gershunov, A. and K. Guirguis, 2012. California heat waves in the present and future. *Geophys. Res. Lett.* <https://doi.org/10.1029/2012GL052979>

Gershunov, A., Shulgina, T., Ralph, F. M., Lavers, D. A. & Rutz, J. J. Assessing the climate-scale variability of atmospheric rivers affecting western North America. *Geophys. Res. Lett.* **44**, 7900–7908 (2017).

Howarth, M.E., C.D. Thorncroft and L.F. Bosart, 2019, Changes in extreme precipitation in the Northeast United States: 1979-2014. *J. Hydromet.* **20**, 673-689. DOI: 10.1175/JHM-D-18-0155.1

Hurst, H. E. (1951), Long term storage capacities of reservoirs, *Trans. Am. Soc. Civ. Eng.*, **116**, 776–808.

Jong, B.-T., Murakami, H., Delworth, T. L., & Cooke, W. F. (2024). Contributions of tropical cyclones and atmospheric rivers to extreme precipitation trends over the Northeast US. *Earth's Future*, **12**, e2023EF004370. <https://doi.org/10.1029/2023EF004370>

Karl, T.R., C.N. Williams, Jr., F.T. Quinlan, and T.A. Boden, 1990: United States Historical Climatology Network (HCN) Serial Temperature and Precipitation Data, Environmental Science Division, Publication No. 3404, Carbon Dioxide Information and Analysis Center, Oak Ridge National Laboratory, Oak Ridge, TN, 389 pp.

Markonis, Yannis, Koutsoyiannis, Demetris (2016). Scale-dependence of persistence in precipitation records. *Nat. Clim. Change* **6**, 399–401.

Mass, C., D. Owens, J. Christy, and R. Conrick, **2024**: The Pacific Northwest heat wave of 25-30 June 2021: Synoptic/Mesoscale conditions and climate perspective. *Weather and Forecasting*, **39**. DOI: 10.1175/WAF-D-23-0154.1.

McKittrick, R. and J.R. Christy, **2019**: Assessing changes in US regional precipitation on multiple time scales. *J. Hydro.* **578**, (2019), DOI.ORG/10.1016/j.jhydrol.2019.124074

Overland, J. E., 2021: Causes of the record-breaking Pacific Northwest heatwave, late June 2021. *Atmosphere*, **12**, 1434, <https://doi.org/10.3390/atmos12111434>.

NCA17, Climate Science Special Report: Fourth National Climate Assessment, Volume I, 2017. Wuebbles, D.J., D.W. Fahey and K.A. Hibbard .eds. U.S. Global Change Research Program. Washington DC, USA. doi: 10.7930/J0J964J6. <https://repository.library.noaa.gov/view/noaa/19486>

NCA23, Fifth National Climate Assessment. Crimmins, A.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, B.C. Stewart, and T.K. Maycock, Eds. U.S. Global Change Research Program, Washington, DC, USA. <https://doi.org/10.7930/NCA5.2023.CH1>.

Null, J. and J. Hulbert, “California Washed Away: The Great Flood of 1862,” *Weatherwise* **60**, no. 1 (2007): 26–30, <https://doi.org/10.3200/wewi.60.1.26-30>.

Pan, M., M. Lu and U. Lall, 2024: Diversity of cross-Pacific atmospheric river main routes. *Nature Com. Earth & Envi.* **5**, 378. <https://www.nature.com/articles/s43247-024-01552-y>

Philip, S. Y., Kew, S. F., van Oldenborgh, G. J., Anslow, F. S., Seneviratne, S. I., Vautard, R., Coumou, D., Ebi, K. L., Arrighi, J., Singh, R., van Aalst, M., Pereira Marghidan, C., Wehner, M., Yang, W., Li, S., Schumacher, D. L., Hauser, M., Bonnet, R., Luu, L. N., Lehner, F., Gillett, N., Tradowsky, J. S., Vecchi, G. A., Rodell, C., Stull, R. B., Howard, R., and Otto, F. E. L.: Rapid attribution analysis of the extraordinary

heat wave on the Pacific coast of the US and Canada in June 2021, *Earth Syst. Dynam.*, 13, 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>, 2022.

Porter, K. et al., *Overview of the Arkstorm Scenario* (Reston, VA: Dept. of the Interior. U.S. Geological Survey, 2011).

Pielke, R. A. et al. Land use/land cover changes and climate: Modeling analysis and observational evidence. *Wiley Interdiscip. Rev. Clim. Chang.* **2**, 828–850 (2011).

Quinlan, F. T., T. R. Karl, and C. N. Williams Jr. (1987), United States Historical Climatology Network (USHCN) serial temperature and precipitation data, NDP-019, Carbon Dioxide Inf. Anal. Cent., Oak Ridge Natl. Lab., U.S. Dep. of Energy, Oak Ridge, Tenn.

USGCRP, 2023: USGCRP Indicators Platform: Heat Waves. U.S. Global Change Research Program. <https://www.globalchange.gov/indicators/heat-waves>

White, R.H., Anderson, S., Booth, J.F. *et al.* The unprecedented Pacific Northwest heatwave of June 2021. *Nat Commun* **14**, 727 (2023). <https://doi.org/10.1038/s41467-023-36289-3>

Weinkle, Jessica, Ryan Maue and Roger Pielke Jr. (2012) Historical Global Tropical Cyclone Landfalls *Journal of Climate* 25(13) 4729–4735 <https://doi.org/10.1175/JCLI-D-11-00719.1>

Tu, Shifei, Zhenzhen Hu, Mei Liang, Wen Zhou, Johnny Chan and Jianjun Xu (2024) Decreasing trend in destructive potential of tropical cyclones in the South Indian Ocean since the mid-1990s. *Communications Earth and Environment* 5:543 <https://www.nature.com/articles/s43247-024-01683-2>

Yang, L., Yang, Y., Shen, Y. *et al.* Urban development pattern's influence on extreme rainfall occurrences. *Nat Commun* **15**, 3997 (2024). <https://doi.org/10.1038/s41467-024-48533-5>.

Zhang, W., Villarini, G., Vecchi, G. A. & Smith, J. A. Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. *Nature* **563**, 384–388 (2018).

1. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge, UK: Cambridge University Press, 2021), Chapter 11, <https://www.ipcc.ch/report/ar6/wg1/chapter/chapter-11/>.
2. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021: The Physical Science Basis. Summary for Policymakers*, in *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2023), <https://www.cambridge.org/core/books/climate-change-2021-the-physical-science-basis/summary-for-policymakers/8E7A4E3AE6C364220F3B76A189CC4D4C>.
3. Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2021*.
4. Ryan N. Maue, *Climatlas: Tropical Cyclones*, accessed May 8, 2025, <https://climatlas.com/tropical/>.
5. Colorado State University, *Realtime Tropical Cyclone Guidance*, Tropical Weather and Climate Research, Department of Atmospheric Science, accessed May 8, 2025, <https://tropical.atmos.colostate.edu/Realtime/index.php>.

6. Gabriel A. Vecchi and Thomas R. Knutson, "Estimating Annual Numbers of Atlantic Hurricanes Missing from the HURDAT Database (1878–1965) Using Ship Track Density," *Journal of Climate* 24, no. 6 (2011): 1736–1746, <https://doi.org/10.1175/2010JCLI3810.1>.
7. National Hurricane Center, *Tropical Cyclone Climatology*, National Oceanic and Atmospheric Administration, accessed May 8, 2025, <https://www.nhc.noaa.gov/climo/images/AtlanticStormTotalsTable.pdf>.
8. Stanley B. Goldenberg et al., "The Recent Increase in Atlantic Hurricane Activity: Causes and Implications," *Science* 293, no. 5529 (July 20, 2001): 474–479, <https://doi.org/10.1126/science.1060040>.
9. Gerald D. Bell and Muthuvel Chelliah, "Leading Tropical Modes Associated with Interannual and Multidecadal Fluctuations in North Atlantic Hurricane Activity," *Journal of Climate* 19, no. 4 (February 15, 2006): 590–612, <https://doi.org/10.1175/JCLI3659.1>.
10. Philip J. Klotzbach et al., "Continental U.S. Hurricane Landfall Frequency and Associated Damage: Observations and Future Risks," *Bulletin of the American Meteorological Society* 99, no. 7 (July 2018): 1359–1376, <https://doi.org/10.1175/BAMS-D-17-0184.1>.
11. NOAA Hurricane Research Division(a), *All U.S. Hurricanes (1851–2019)*, Atlantic Oceanographic and Meteorological Laboratory, National Oceanic and Atmospheric Administration, accessed May 8, 2025, https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html.
12. Philip J. Klotzbach et al., "Continental U.S. Hurricane Landfall Frequency and Associated Damage."
13. Gabriele Villarini, Gabriel A. Vecchi, and James A. Smith, "U.S. Landfalling and North Atlantic Hurricanes: Statistical Modeling of Their Frequencies and Ratios," *Monthly Weather Review* 140, no. 1 (January 2012): 44–65, <https://doi.org/10.1175/MWR-D-11-00063.1>.
14. NOAA Hurricane Research Division(b), *Most Intense (3, 4, 5) Continental United States Hurricanes: 1851 - 1970, and 1983-2023*, Atlantic Oceanographic and Meteorological Laboratory, National Oceanic and Atmospheric Administration, accessed May 8, 2025, https://www.aoml.noaa.gov/hrd/hurdat/most_intense.html.

Charles Apple, "1910 Fire - the Big Burn across Montana and Idaho," *Spokesman.com* (The Spokesman-Review, January 21, 2020), <https://www.spokesman.com/stories/2020/jan/19/1910-fire-big-burn-across-montana-and-idaho/>.

National Forest Foundation "Blazing Battles: The 1910 Fire and Its Legacy," National Forest Foundation, accessed September 28, 2022, <https://www.nationalforests.org/our-forests/your-national-forests-magazine/blazing-battles-the-1910-fire-and-its-legacy>.

Forest History Society "The 1910 Fires," Forest History Society, accessed September 28, 2022, <https://foresthistory.org/research-explore/us-forest-service-history/policy-and-law/fire-u-s-forest-service/famous-fires/the-1910-fires/>.

US Forest Service (2022) "Managing Fire," US Forest Service, September 28, 2022, <https://www.fs.usda.gov/science-technology/fire>.

Lauren Sommer (2016), "Let It Burn: The Forest Service Wants to Stop Putting out Some Fires," *KQED*, November 7, 2016, <https://www.kqed.org/science/1134217/let-it-burn-the-forest-service-wants-to-stop-putting-out-some-fires>.

Stephens, Scott L et al., (2021) "Fire, Water, and Biodiversity in the Sierra Nevada: A Possible Triple Win," *Environmental Research Communications* 3, no. 8 (August 6, 2021): p. 081004, <https://doi.org/10.1088/2515-7620/ac17e2>.

Webarchive.org (nd) Archive of NIFC fire data
https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html.

National Interagency Fire Center (2024) Wildfire statistics. <https://www.nifc.gov/fire-information/statistics/wildfires>

Koutsoyiannis, D (2013) Hydrology and Change, *Hydrological Sciences Journal*, 58 (6), 1177–1197, [doi:10.1080/02626667.2013.804626](https://doi.org/10.1080/02626667.2013.804626).

7 Changes in Sea level

Chapter Summary

Since 1900, global average sea level has risen by about 8". Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. US tide gauge measurements shown herein reveal no obvious acceleration beyond the historical average rate of sea level rise.

7.1 U.S. coastal sea level rise

Arguably the most important climate impact driver that is unambiguously associated with increasing temperatures is global sea level rise. Global warming increases sea level rise through thermal expansion of the volume of sea water and melting of glaciers and ice sheets. Another factor that influences sea level variations is land water storage. Regional sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Local sea level rise is further influenced by vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018. The rate of sea level rise has accelerated in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018.¹ The rate of global sea level rise is estimated to be 0.12 inches/year (for reference: 0.12 in is the height of two stacked pennies).²

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

Observed and predicted rates of mean global sea level rise may have little relevance for specific locations³. In Canada and Alaska (and also northern Washington), sea level is actually decreasing,

¹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.

² “Rising Waters: How NASA Is Monitoring Sea Level Rise,” NASA (NASA), accessed May 19, 2022, <https://www.nasa.gov/specials/sea-level-rise-2020/>.

³ <https://tidesandcurrents.noaa.gov/sltrends/>

owing to uplift from glacial rebound. Most of the Pacific coast has rates of sea level rise of 0 to 0.12 inches/year. The largest rates of sea level rise are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the rise in the volume of seawater with local vertical land motion. Hence in examining local sea level changes, it is important to also consider the local vertical land motion. Absolute local sea level rise is the sum of relative sea level rise and the local vertical land motion.

A wide range of processes can cause vertical land motion along the coasts, having amplitudes comparable to the sea level signals expected from land-ice melting or ocean thermal expansion. Vertical land motion on the coasts can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise. Local changes in sea level vary considerably from place to place and can deviate substantially from the rate of global mean sea level change.⁴ Human activities triggering subsidence are soil drainage (e.g. for urban development purposes) or subsurface mining of resources such as groundwater, oil or gas. The magnitude of relative sea level rise caused by human activities is often considerable. Local vertical land motion of relevance to local sea level change is best measured using a Global Positioning System (GPS) station located in the location as the tide gauge.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR)⁵ and the vertical land motion (VLM)^{6, 7,8} measurements. The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local sinking of the land. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Table 7.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

⁴ Wöppelmann, G., and M. Marcos (2016), Vertical land motion as a key to understanding sea level change and variability, *Rev. Geophys.*, 54, 64–92.

⁵ NOAA Tides & Currents, Relative Sea Level Trends - <https://tidesandcurrents.noaa.gov/sltrends/>

⁶ NAS (2012) *Sea-Level Rise for the Coasts of California, Oregon and Washington: Past, Present, and Future*. Appendix A: Vertical Land Motion and Sea-Level Data Along the West Coast of the United States. National Academies Press, NAP.edu/10766.

⁷ Letetrel, C, M Karpytchev, MN Bouin et al (2015) Estimation of vertical land movement rates along the coasts of the Gulf of Mexico over the past decades. *Continental Shelf Research*, 111, 42-51.

⁸ Karegar, MA, TH Dixon, SE Engelhart (2016), Subsidence along the Atlantic Coast of North America: Insights from GPS and late Holocene relative sea level data, *Geophys. Res. Lett.*, 43, 3126–3133, doi:10.1002/2016GL068015.

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.1). As shown in Table 7.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent rate of absolute sea level rise of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year.⁹ Landfill zones are sinking due to soil compaction, at a rate as much as one-half inch per year, threatening coastal infrastructure including the San Francisco International Airport. The problems in the San Francisco Bay area have been caused primarily by sinking in landfill regions that were formerly wetlands, not by the slow creep of global sea level rise.

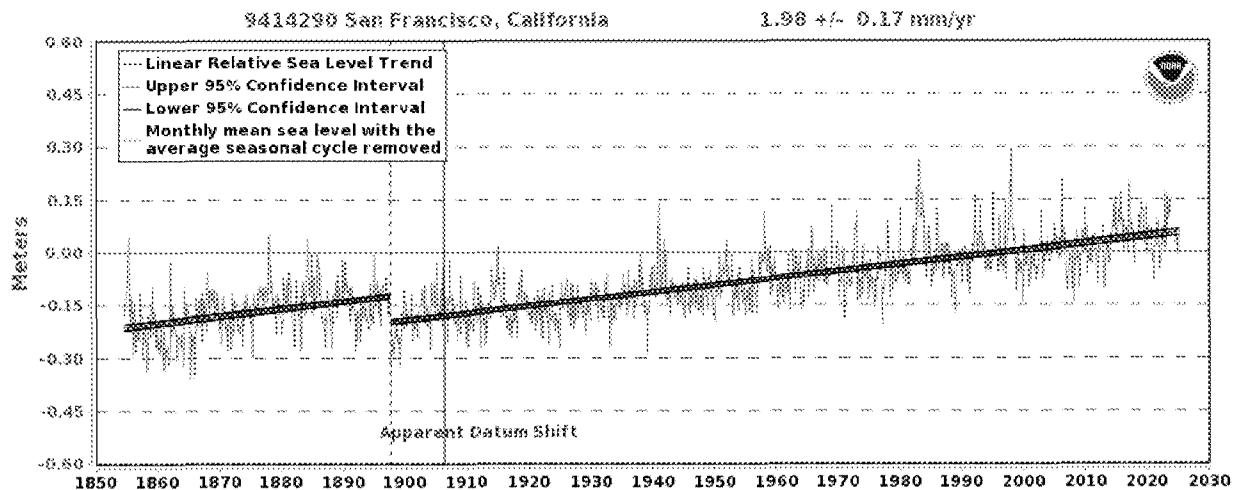


Figure 7.1. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.2). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding a value of absolute sea level rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region has occurred as a direct result of groundwater withdrawals.¹⁰ This caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes are traditionally the major concern in the region. The 1900 hurricane that struck

⁹ Shirzaei, M, R Burgmann (2018) Global climate change and local land subsidence exacerbate inundation risk to the San Francisco Bay Area. *Science Advances*, 4, eaap9234

¹⁰ Kasmarek, M.C., and Ramage, J.K., 2017, Water-level altitudes 2017 and water-level changes in the Chicot, Evangeline, and Jasper aquifers and compaction 1973–2016 in the Chicot and Evangeline aquifers, Houston-Galveston region, Texas: U.S. Geological Survey Scientific Investigations Report 2017–5080, 32 p., <https://doi.org/10.3133/sir20175080>.

Galveston and killed between 6,000 and 12,000 people is still considered the United States' deadliest natural disaster.¹¹ Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula literally removing significant portions of the land mass.¹² While only 17 people were killed in Texas, property damage exceeded \$50 billion.¹³ In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages.¹⁴

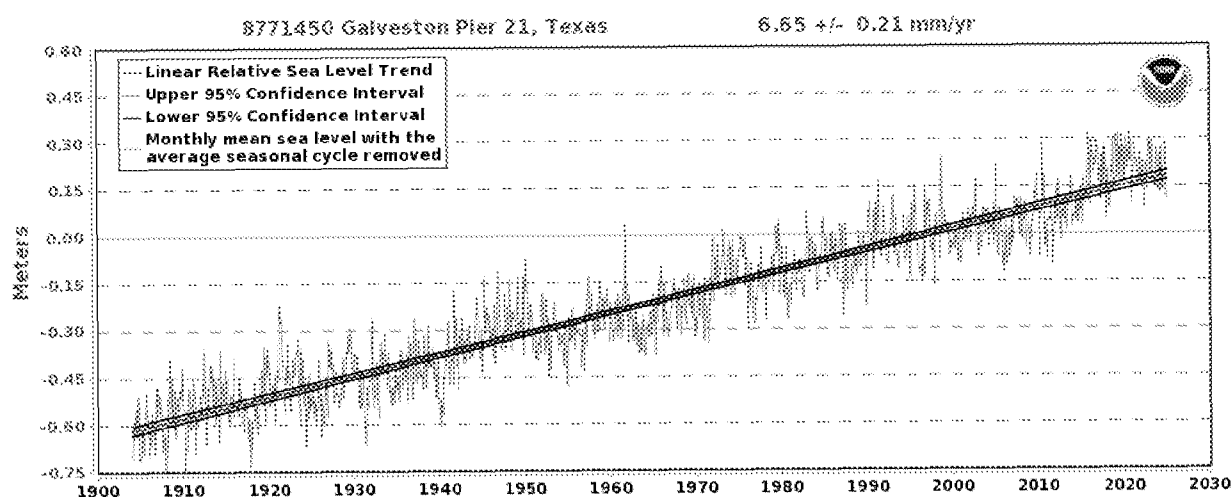


Figure 7.2. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

There are long-term tide gauge measurements at Grand Isle, Louisiana, respectively estimating that sea level has risen slightly more than 3 feet over the last 100 years and at an average rate of 0.36 inches/year (Figure 7.3). Vertical land motion (subsidence) is estimated -0.28 inches/year at Grand Isle. From Table 7.1, the absolute sea level rise is +0.08 inches/year at Grand Isle.

¹¹ Weems, John Edward, "Galveston Hurricane of 1900", Texas State Historical Association, (March 15, 2016) <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.

¹² "Galveston County, Texas, Faces Sea Level Rise and Storms", Union of Concerned Scientists, (June 23, 2017) <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.

¹³ White, Audrey, "Galveston Still Healing 5 Years After Hurricane Ike", The Texas Tribune, (April 26, 2013) <https://www.texastribune.org/2013/04/26/galveston-still-healing-5-years-after-hurricane-ike/>.

¹⁴ NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

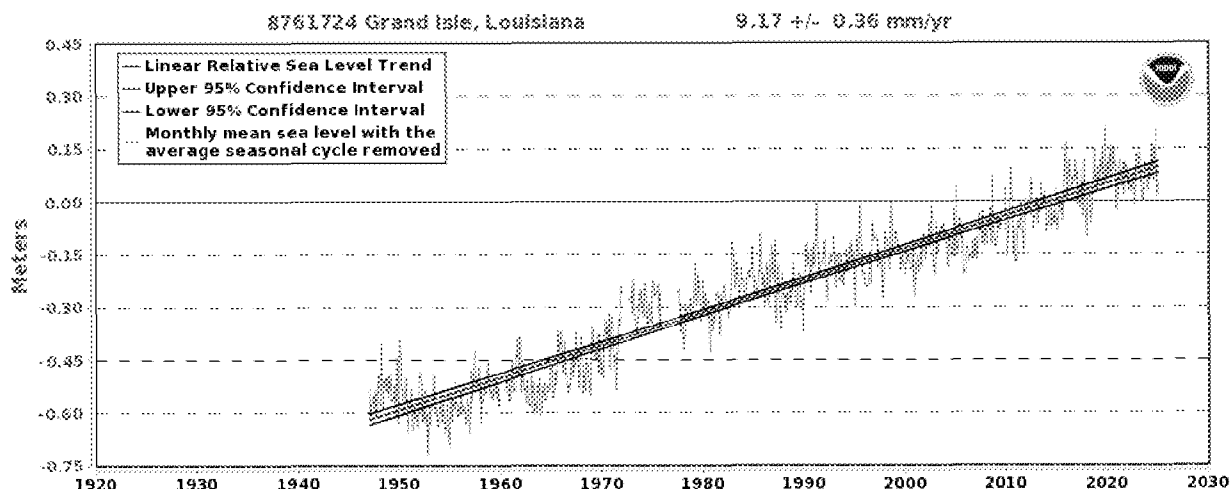


Figure 7.3. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. Due to the construction of dams in the basin since the 1950s, the suspended sediment load of the Mississippi River has decreased by ~50%.¹⁵ A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year.¹⁶ For a city whose elevation averages one to two feet below sea level, sea level rise from human caused warming is not the dominant driver for the problems that New Orleans is facing.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. In New York City, relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.4). Vertical land motion in the New York City area is occurring at a rate of -0.05 inches/year (subsidence), corresponding to roughly 5 inches per century. From Table 7.1, the absolute rate of sea level rise at The Battery location is 0.06 inches/year, or about 55% of the measured relative sea level rise.

¹⁵ Jillian M. Maloney et al., “Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation,” *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.

¹⁶ Jaap H. Nienhuis et al., “A New Subsidence Map for Coastal Louisiana,” *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.

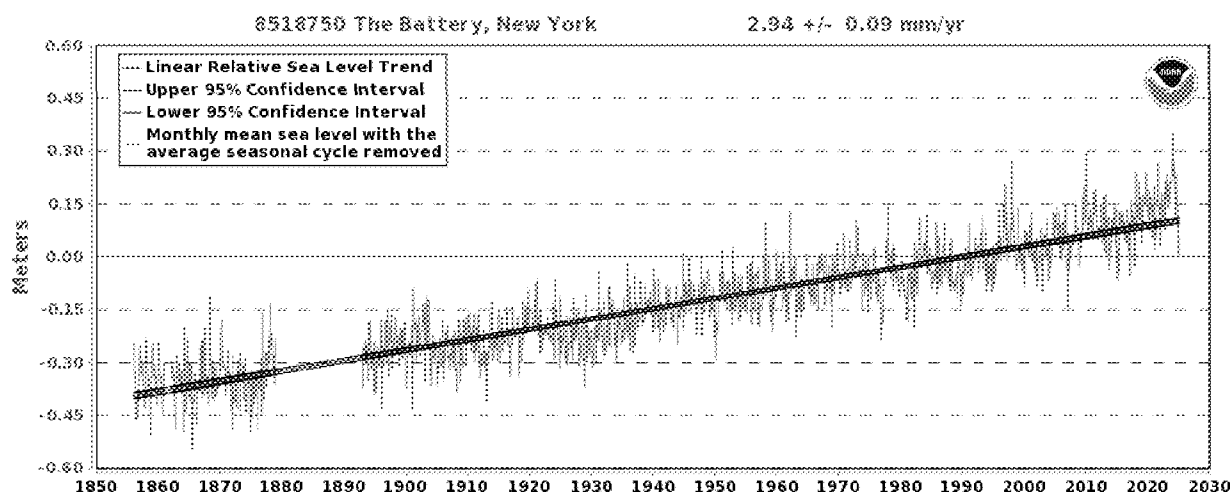


Figure 7.4. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Hurricane Sandy, New York has developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York*.¹⁷ A broad range of coastal protection measures are outlined that match the risks facing a given area: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

7.2 Sea level rise projections

The concern over sea level rise is not about the 8 inches or so that global mean sea level has risen since 1900. Rather, the concern is about projections of 21st century sea level rise based on climate model-based projections of human-caused global warming.

The IPCC AR6 finds that there is *high agreement* across published global mean sea level projections for 2050 and there is little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period.¹⁸

Conversely, there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range)

¹⁷ City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.

¹⁸ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.

under the medium emissions scenario SSP2–4.5.¹⁹ There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 7.1-7.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

¹⁹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change.”

8 Uncertainties in Climate Change Attribution

Chapter summary

“Attribution” refers to determining cause regarding some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming: inadequate assessment of natural climate variability, and use of inappropriate statistical methods.

Attribution of extreme weather events is challenging due to their rarity. The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to event probability (return times), magnitude and frequency are not generally considered accurate owing to data limitations and are made with low confidence. The 2021 Western North America Heatwave event provides a good illustration of the perils of making hasty attribution claims.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause.¹ As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

¹ Note that the IPCC definition of “climate change” allows for both natural and human causes. This differs from the UNFCCC definition (and common usage), where the term is limited to human causes.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement: (Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series

can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to

increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 5, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 *Natural climate variability*

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by -0.1°C to $+0.1^{\circ}\text{C}$, and internal variability has changed it by -0.2°C to $+0.2^{\circ}\text{C}$ – on average having essentially no net impact on the warming since 1850-1900. This minimal contribution of natural variability has been disputed by a number of publications that question the magnitudes of solar variability and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO_2 is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco

Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Nino-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly

to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to $+0.2^{\circ}\text{C}$ (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C . Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares.

The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-

existent – hence reducing confidence in the results.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest when assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-

related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first column of Table 12.12 in Ranasinghe et al. (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Out of the 33 weather impact categories an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Columns 2 and 3 of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We omitted these columns in part because they refer to whether climate models project signals will be detectable in the data, but this is a very different question than the one that concerns us here, namely whether a signal has been detected in historical data. Additionally, as we discuss in Chapter 3 the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Even still it is worth noting that the omitted columns in AR6 Table 12.12 indicate most weather impacts are not expected to exhibit an anthropogenic signal this century.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	3
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fire weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	13
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease
Medium confidence of decrease
Low confidence in direction of change
Medium confidence of increase
High confidence of increase

Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

As we discussed in Chapter 6 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.5 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA's tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics

questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 6, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993).

For instance, there might be an “ordinary” weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second “heatwave” regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case study from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today's climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a $\sim 1.4^{\circ}\text{C}$ – 1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F . While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

1. Intergovernmental Panel on Climate Change. *IPCC Glossary*. Accessed May 2, 2025. <https://apps.ipcc.ch/glossary/>.
2. G. C. Hegerl et al., “Understanding and Attributing Climate Change,” in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 663–745.
3. J. T. Houghton et al., eds., *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press, 2001), 1–881.
4. W. Cramer et al., “Detection and Attribution of Observed Impacts,” in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. C. B. Field et al. (Cambridge: Cambridge University Press, 2014), 979–1037.
5. Intergovernmental Panel on Climate Change, *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S. Solomon et al. (Cambridge: Cambridge University Press, 2007), 10.
6. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker et al. (Cambridge: Cambridge University Press, 2013), 17.

7. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Cambridge: Cambridge University Press, 2021), 10.
8. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate,” *Research in Astronomy and Astrophysics* 21, no. 6 (2021): 131, <https://doi.org/10.1088/1674-4527/21/6/131>.
9. Willie Soon et al., “The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data,” *Climate* 11, no. 9 (2023): 179, <https://doi.org/10.3390/cli11090179>.
10. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records,” *Geoscience Frontiers* 14, no. 6 (November 2023): 101650, <https://doi.org/10.1016/j.gsf.2023.101650>.
11. Gunnar Myhre et al., “Anthropogenic and Natural Radiative Forcing,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge: Cambridge University Press, 2014), 659–740, <https://doi.org/10.1017/CBO9781107415324.018>.
12. Sergey K. Gulev et al., “Changing State of the Climate System,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. V. Masson-Delmotte et al. (Geneva: Intergovernmental Panel on Climate Change, 2021), 287–422.
11. Katja Matthes et al., “Solar Forcing for CMIP6 (v3.2),” *Geoscientific Model Development* 10, no. 6 (June 22, 2017): 2247–2302, <https://doi.org/10.5194/gmd-10-2247-2017>.
12. Mike Lockwood, “Solar Influence on Global and Regional Climates,” *Surveys in Geophysics* 33, no. 3–4 (May 16, 2012): 503–534, <https://doi.org/10.1007/s10712-012-9181-3>.
13. Ronan Connolly et al., “How Much Has the Sun Influenced Northern Hemisphere Temperature Trends? An Ongoing Debate.”
14. Nicola Scafetta et al., “Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018,” *Remote Sensing* 11, no. 21 (November 1, 2019): 2569, <https://doi.org/10.3390/rs11212569>.
14. V. M. Velasco Herrera, B. Mendoza, and G. Velasco Herrera, “Reconstruction and Prediction of the Total Solar Irradiance: From the Medieval Warm Period to the 21st Century,” *New Astronomy* 34 (January 2015): 221–233, <https://doi.org/10.1016/j.newast.2014.07.009>.
15. Theodosios Chatzistergos, Natalie A. Krivova, and Kok Leng Yeo, “Long-Term Changes in Solar Activity and Irradiance,” *Journal of Atmospheric and Solar-Terrestrial Physics* 252 (November 2023): 106150, <https://doi.org/10.1016/j.jastp.2023.106150>.
16. S. K. Solanki et al., “Unusual Activity of the Sun during Recent Decades Compared to the Previous 11,000 Years,” *Nature* 431, no. 7012 (October 28, 2004): 1084–1087, <https://doi.org/10.1038/nature02995>.
17. I. G. Usoskin, S. K. Solanki, and G. A. Kovaltsov, “Grand Minima and Maxima of Solar Activity: New Observational Constraints,” *Astronomy & Astrophysics* 471, no. 1 (June 6, 2007): 301–309, <https://doi.org/10.1051/0004-6361:20077704>.
18. Werner K. Schmutz, “Changes in the Total Solar Irradiance and Climatic Effects,” *Journal of Space Weather and Space Climate* 11 (2021): 40, <https://doi.org/10.1051/swsc/2021016>.

19. Nicola Scafetta, “Discussion on Climate Oscillations: CMIP5 General Circulation Models versus a Semi-Empirical Harmonic Model Based on Astronomical Cycles,” *Earth-Science Reviews* 126 (November 2013): 321–357, <https://doi.org/10.1016/j.earscirev.2013.08.008>.
20. Frank Stefani, “Solar and Anthropogenic Influences on Climate: Regression Analysis and Tentative Predictions,” *Climate* 9, no. 11 (November 3, 2021): 163, <https://doi.org/10.3390/cli9110163>.
21. Ronan Connolly et al., “Challenges in the Detection and Attribution of Northern Hemisphere Surface Temperature Trends Since 1850,” *Research in Astronomy and Astrophysics* 23, no. 10 (2023): 105015, <https://doi.org/10.1088/1674-4527/acf18e>.
22. Nicola Scafetta, “Empirical Assessment of the Role of the Sun in Climate Change Using Balanced Multi-Proxy Solar Records.”
24. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis*.
25. Intergovernmental Panel on Climate Change, *Climate Change 2021: The Physical Science Basis*.
26. Ibid.
27. J. D. McLean, C. R. de Freitas, and R. M. Carter, “Influence of the Southern Oscillation on Tropospheric Temperature,” *Journal of Geophysical Research: Atmospheres* 114, no. D14 (July 23, 2009): D14104, <https://doi.org/10.1029/2008JD011637>.
28. Ka-Kit Tung and Jiansong Zhou, “Using Data to Attribute Episodes of Warming and Cooling in Instrumental Records,” *Proceedings of the National Academy of Sciences* 110, no. 6 (January 23, 2013): 2058–2063, <https://doi.org/10.1073/pnas.1212471110>.
29. Petr Chylek et al., “The Role of Atlantic Multi-Decadal Oscillation in the Global Mean Temperature Variability,” *Climate Dynamics* 47, no. 9–10 (February 20, 2016): 3271–3279, <https://doi.org/10.1007/s00382-016-3025-7>.
30. Nicola Scafetta, “Reconstruction of the Interannual to Millennial Scale Patterns of the Global Surface Temperature,” *Atmosphere* 12, no. 2 (2021): 147, <https://doi.org/10.3390/atmos12020147>.
31. Ross McKittrick, “Checking for Model Consistency in Optimal Fingerprinting: A Comment,” *Climate Dynamics* 58, no. 1–2 (2022): 405–411, <https://doi.org/10.1007/s00382-021-05913-7>.
32. M. R. Allen and S. F. B. Tett, “Checking for Model Consistency in Optimal Fingerprinting,” *Climate Dynamics* 15, no. 6 (1999): 419–434, <https://doi.org/10.1007/s003820050291>.
33. Ross McKittrick, Timothy Vogelsang, and John Christy, “Temperature Trends, Climate Attribution and the Nonstationarity Question,” *Earth System Dynamics Discussions* (2023): <https://doi.org/10.5194/esd-2023-11>.
34. Ross McKittrick, “Total Least Squares Bias in Climate Fingerprinting Regressions with Heterogeneous Noise Variances and Correlated Explanatory Variables,” *Environmetrics* 35, no. 2 (March 2024): e2835, <https://doi.org/10.1002/env.2835>.
35. S. Seneviratne et al., “Chapter 11: Weather and Climate Extreme Events in a Changing Climate.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1513–1766. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.013>.
36. R. Ranasinghe et al., “Chapter 12: Climate Change Information for Regional Impact and for Risk Assessment.” In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V.

- Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al., 1767–1926. Cambridge: Cambridge University Press, 2021. <https://doi.org/10.1017/9781009157896.014>.
37. National Academies of Sciences, Engineering, and Medicine. *Attribution of Extreme Weather and Climate Events and Their Impacts*. Washington, DC: The National Academies Press, forthcoming. <https://www.nationalacademies.org/our-work/attribution-of-extreme-weather-and-climate-events-and-their-impacts>.
 38. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021: Synoptic/Mesoscale Conditions and Climate Perspective,” *Weather and Forecasting* 39, no. 2 (February 2024): 275–291, <https://doi.org/10.1175/WAF-D-23-0154.1>.
 39. World Weather Attribution. “Western North American Extreme Heat Virtually Impossible without Human-Caused Climate Change.” July 7, 2021. <https://www.worldweatherattribution.org/western-north-american-extreme-heat-virtually-impossible-without-human-caused-climate-change/>.
 40. S.Y. Philip et al., “Rapid Attribution Analysis of the Extraordinary Heatwave on the Pacific Coast of the US and Canada June 2021,” *Earth System Dynamics* 13, no. 4 (December 8, 2022): 1689–1713, <https://doi.org/10.5194/esd-13-1689-2022>.
 41. C. Mass et al., “The Pacific Northwest Heat Wave of 25–30 June 2021.”
 42. Emily Bercos-Hickey et al., “Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave,” *Geophysical Research Letters* 49, no. 23 (December 2022): e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
 43. Judea Pearl, *Causality* (Cambridge: Cambridge University Press, 2009).
 44. Geert Jan van Oldenborgh et al., “Attributing and Projecting Heatwaves Is Hard: We Can Do Better,” *Earth’s Future* 10, no. 6 (June 2022): e2021EF002271, <https://doi.org/10.1029/2021EF002271>.
 45. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming,” NOAA Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division, 2017, <https://www.aoml.noaa.gov/hrd/Landsea/harvey-global-warming.pdf>.
 46. David M. Roth, “Tropical Cyclone Rainfall for the North Atlantic Basin,” Weather Prediction Center, National Oceanic and Atmospheric Administration, 2017, <https://www.wpc.ncep.noaa.gov/tropical/rain/tcmaxima.html>.
 47. Geert Jan van Oldenborgh et al., “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017,” *Environmental Research Letters* 12, no. 12 (December 2017): 124009, <https://doi.org/10.1088/1748-9326/aa9ef2>.
 48. Kerry Emanuel, “Assessing the Present and Future Probability of Hurricane Harvey’s Rainfall,” *Proceedings of the National Academy of Sciences* 114, no. 48 (November 28, 2017): 12681–12684, <https://doi.org/10.1073/pnas.1716222114>.
 49. Mark D. Risser and Michael F. Wehner, “Attributable Human-Induced Changes in the Likelihood and Magnitude of the Observed Extreme Precipitation During Hurricane Harvey,” *Geophysical Research Letters* 44, no. 24 (December 2017): 12,457–12,464, <https://doi.org/10.1002/2017GL075888>.
 50. Kevin E. Trenberth et al., “Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation,” *Earth’s Future* 6, no. 5 (May 2018): 730–744, <https://doi.org/10.1029/2018EF000825>.
 51. Christopher W. Landsea, “Hurricane Harvey’s Rainfall and Global Warming.”
 52. Yog Aryal et al., “Long Term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño–Southern

Oscillation,” *Journal of Hydrology* 559 (2018): 698–710,
<https://doi.org/10.1016/j.jhydrol.2018.02.072>.

Ranasinghe, R., A.C. Ruane, R. Vautard, N. Arnell, E. Coppola, F.A. Cruz, S. Dessai, A.S. Islam, M. Rahimi, D. Ruiz Carrascal, J. Sillmann, M.B. Sylla, C. Tebaldi, W. Wang, and R. Zaaboul, (2021): Climate Change Information for Regional Impact and for Risk Assessment. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1767–1926, doi:[10.1017/9781009157896.014](https://doi.org/10.1017/9781009157896.014).

Jones, Gareth, Peter A. Stott and John F.B. Mitchell (2016) Uncertainties in the Attribution of Greenhouse Gas Warming and Implications for Climate Prediction. *Journal of Geophysical Research-Atmospheres* 121(12) 6969—6992 <https://doi.org/10.1002/2015JD024337>.

Kravtsov, S., A. Westgate and A. Gavrilov (2024) Global-scale multidecadal variability in climate models and observations, part II: The stadium wave. *Climate Dynamics* Volume 62, pages 10281–10306 <https://link.springer.com/article/10.1007/s00382-024-07451-4>

Weinkle, Jessica (2025) Carnival mirrors: How concentrated is the event attribution literature? Substack essay <https://jessicaweinkle.substack.com/p/how-big-is-the-event-attribution>

Chen, Chung and Lon-Mu Liu (1993) Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association* Vol. 88, No. 421 (Mar., 1993), pp 284—297. <http://www.jstor.org/stable/2290724>

Sardeshmukh, Prashant D., Gilbert P. Compo and Cécile Penland (2015) Need for Caution in Interpreting Extreme Weather Statistics *Journal of Climate* 28(23) 9166–9187 <https://journals.ametsoc.org/view/journals/clim/28/23/jcli-d-15-0020.1.xml>

Visser, H. and A.C. Petersen (2012) Inferences on weather extremes and weather-related disasters: a review of statistical methods *Climates of the Past* 8, 265–286 <https://cp.copernicus.org/articles/8/265/2012/cp-8-265-2012.pdf>

Miralles, Ophélie and Anthony Davison (2023) Timing and spatial selection bias in rapid extreme event attribution. *Weather and Climate Extremes* 41 100584 <https://doi.org/10.1016/j.wace.2023.100584>

Barlow, Anna Maria, Chris Sherlock and Jonathan Tawn (2020) Inference for Extreme Values Under Threshold-Based Stopping Rules. *Journal of the Royal Statistical Society Series C* August 2020, Pages 765–789, <https://doi.org/10.1111/rssc.12420>

Zeder, J., Sippel, S., Pasche, O. C., Engelke, S., & Fischer, E. M. (2023). The effect of a short observational record on the statistics of temperature extremes. *Geophysical Research Letters*, 50, e2023GL104090. <https://doi.org/10.1029/2023GL104090>

Fleishman, E., editor. (2023). Sixth Oregon Climate Assessment. Oregon Climate Change Research Institute, Oregon State University, Corvallis, Oregon. <https://blogs.oregonstate.edu/occri/oregon-climate-assessments> .

McKinnon, K. and I. Simpson (2022) How Unexpected Was the 2021 Pacific Northwest Heatwave? Geophysical Research Letters, 49, e2022GL100380. <https://doi.org/10.1029/2022GL100380>

Bercos-Hickey et al. (2022) Anthropogenic Contributions to the 2021 Pacific Northwest Heatwave. Geophysical Research Letters 49 <https://doi.org/10.1029/2022GL099396>

Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay <https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>

9 Climate change and US agriculture

Chapter summary

There is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behavior by farmers, has been beneficial on its own for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptive responses of farmers are taken into account the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached similar conclusions to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming. Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land

prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a major driver of plant growth so this omission biases the analysis towards underestimation of the benefits of climate change on agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm cause an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels.

But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted US crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

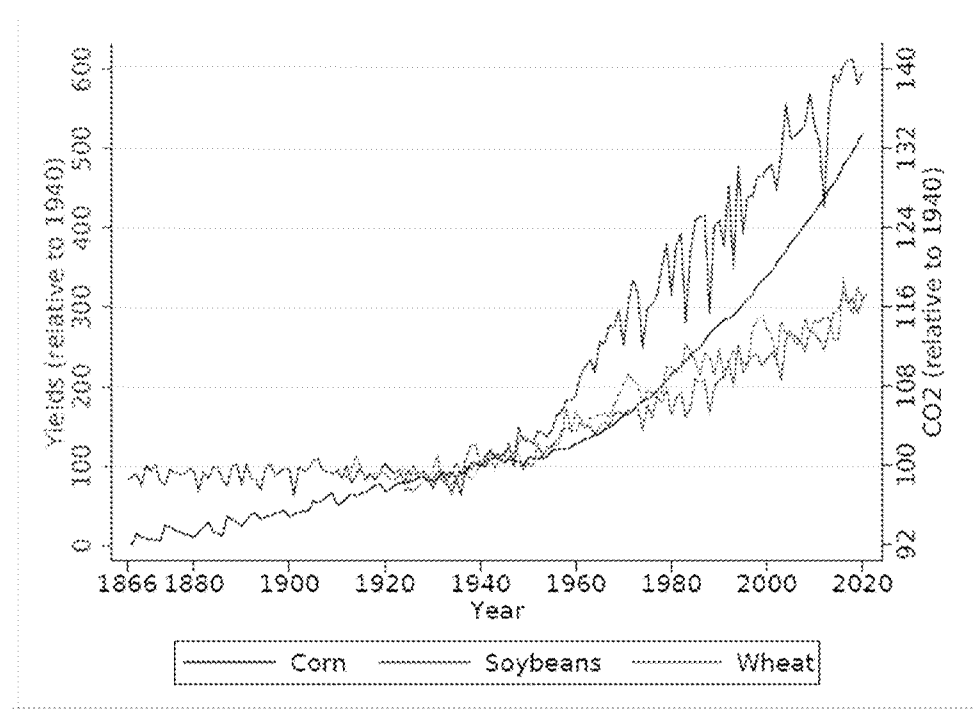


Figure 9.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100.
Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to heat. Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al. also

reported that negative yield impacts on wheat and soybean were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

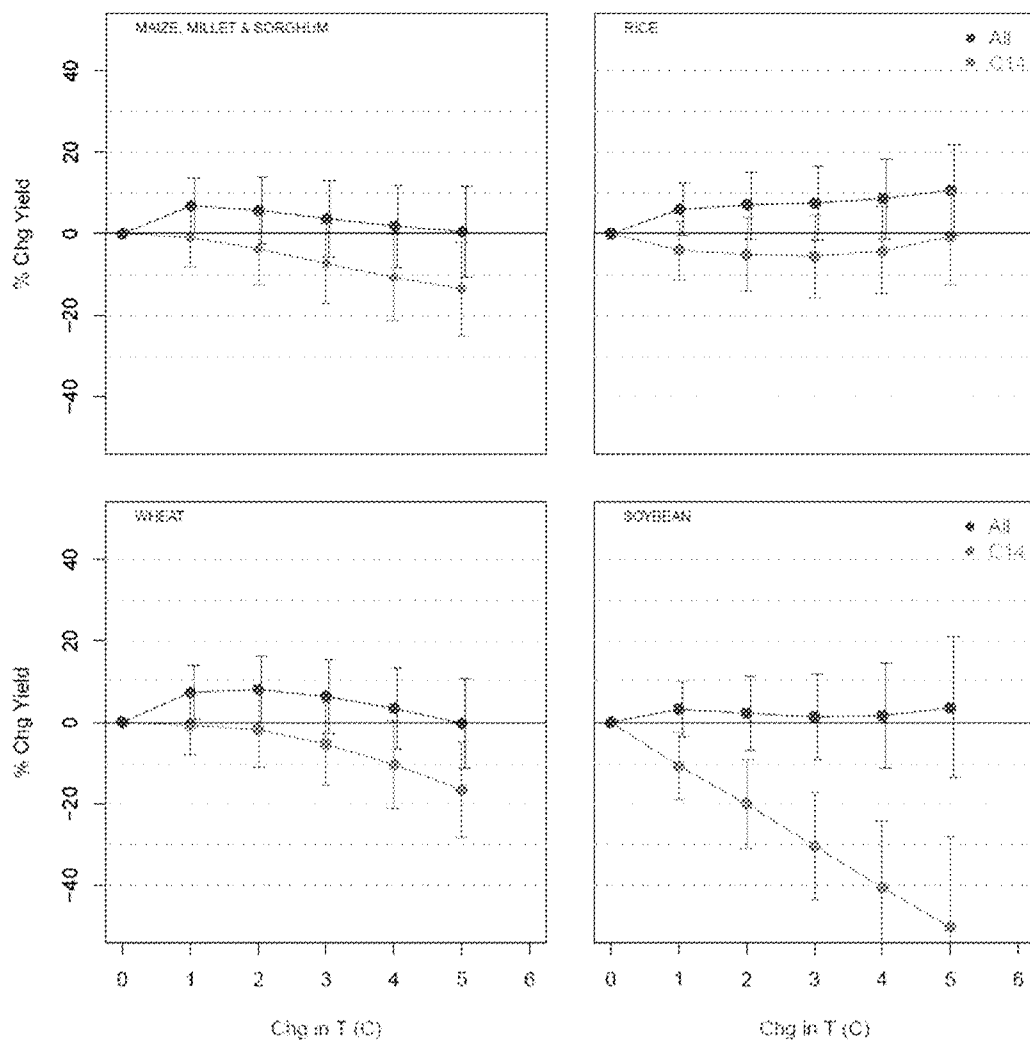


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

Deschênes, Olivier and Michael Greenstone (2007) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather *American Economic Review*. Feb 2007, Vol. 97, No. 1: Pages 354-385

Deschênes, Olivier and Michael Greenstone (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply to Comment *American Economic Review*. 102, no. 7: 3761-3773. <http://hdl.handle.net/1721.1/82641>

Ortiz-Bobea, Ariel (2019) The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture. *American Journal of Agricultural Economics*. 102 (3), 934-959.

Schlenker, Wolfram and Michael Roberts (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* 106 (37) 15594-15598 <https://doi.org/10.1073/pnas.0906865106>

12 Climate change, the economy and the Social Cost of Carbon

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points at present does not justify major revisions to SCC estimates.

12.1 Climate change and economic growth

12.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects of climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021).

For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future

2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus' Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models. (AR6 offers 2.7°C in 2100 under a moderate emissions scenario.)

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we scale back only the lowest-value fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

12.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell et al. (2012, herein DJ012) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJ012 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJ012-type results on the same subset of countries as used in DJ012 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJ012 data set and applied an estimator robust to mixed sample frequencies, finding that while

temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJ012 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is taken into account the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 398% growth.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. The following figure, from a 2023 OMB-CEA [report](#), shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.

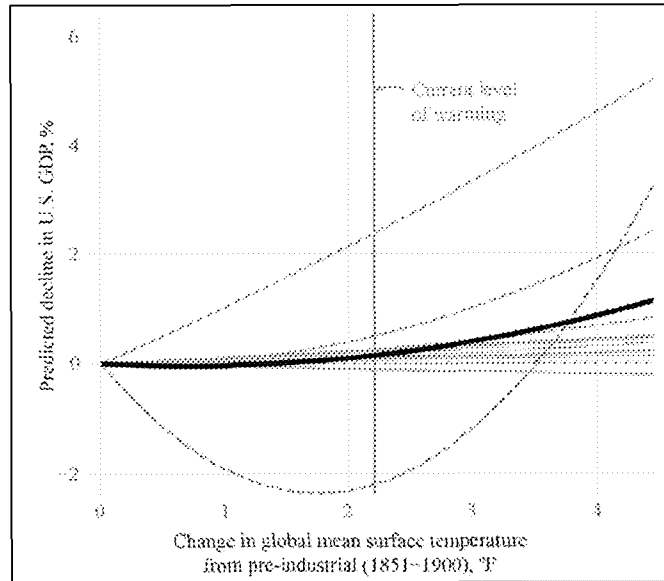


Figure 12.1: Decline in US GDP per degree of warming. Source: XX

12.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

Sidebar: finding the optimal emissions price

On its own the SCC is not the appropriate price to attach to CO₂ emissions for the purpose of optimal emissions control but it can be converted into an optimal tax rate by scaling it by a parameter called the Marginal Cost of Public Funds (MCPF). The theory behind this was first derived by Sandmo (1975) and has been reiterated many times since then by other economists working on the topic (e.g. Parry et al. 1999). The MCPF is the cost in terms of lost private economic welfare of raising public revenue by one dollar and always exceeds unity. If a jurisdiction does not use a carbon tax, this formula still indicates the upper bound on the amount emitters should spend on abatement options at the margin along the optimal policy path. Regulations should be imposed only insofar as they do not impose marginal abatement costs in excess of the optimal tax rate.

12.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO2 levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO2 emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

12.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC's guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter 9). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as

discussed in Chapter 10, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

12.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

12.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz et al. 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For

example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly's wings (Shen et al. 2014). The term "tipping point" is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth's climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon 2023).

The possible existence of bifurcations in the Earth's climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al 2024) and indeed may not be able to since one implication of the "butterfly effect" is the existence of predictability boundaries of nonlinear systems (Palmer et al. 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the "tipping point" concept in discussions of climate change (see <https://report-2023.global-tipping-points.org/what-is-a-tipping-point/> for example). As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023). It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate "tipping point" is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only a modest increase in the SCC value in the 21st century.

12.2.5 Are there alternatives?

To conclude, it is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the weaknesses of the SCC concept don't mean that other regulatory measures are inherently better or more efficient. Many climate regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) end up costing far more per tonne of abatement than a simple price on carbon emissions.

- Barrage, Lint and William Nordhaus (2024) Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. *Proceedings of the National Academy of Sciences* 121 (13) e2312030121 <https://doi.org/10.1073/pnas.2312030121>
- Berg, Kimberly, Chadwick C Curtis and Nelson Mark. (2021) GDP and temperature: Evidence on cross-country response heterogeneity. NBER Working Paper 31327 June 2023 <http://www.nber.org/papers/w31327>
- Chris Thounge (2017) "Is It Time to Kill Off the Social Cost of Carbon?" Cambridge Econometrics Blog, September 14, 2017, <https://www.camecon.com/blog/time-kill-social-cost-carbon/>.
- Daisy Dunne (2017), "Q&A: The Social Cost of Carbon," Carbon Brief, February 14, 2017, <https://www.carbonbrief.org/qa-social-cost-carbon/>
- McKittrick, Ross R. (2025) Extended Crop Yield Meta-analysis Data do not Support Upward SCC Revision. *Scientific Reports* 15 article 5575 <https://www.nature.com/articles/s41598-025-90254-2>
- Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>
- Nordhaus, W. (1993) Optimal Greenhouse-Gas Reductions and Tax Policy in the "DICE" Model *American Economic Review* Vol. 83, No. 2, (Papers and Proceedings) pp.313-317.
- Parry, Ian, Roberton C. Williams III and Lawrence H. Goulder (1999). "When Can Carbon Abatement Policies Increase Welfare? The Fundamental Role of Distorted Factor Markets." *Journal of Environmental Economics and Management* 37: 52—84.
- Resources for the Future (2025) "Social Cost of Carbon Explorer," Resources for the Future website, accessed April 22, 2025, <https://www.rff.org/publications/data-tools/scc-explorer/>.
- Roe, Gerard H. and Yoram Bauman (2013) Climate Sensitivity: Should the climate tail wag the policy dog? *Climatic Change* (2013) 117:647–662 DOI 10.1007/s10584-012-0582-6
- Sandmo, Agnar (1975) "Optimal Taxation in the Presence of Externalities." *Swedish Journal of Economics* 77 (1), 86–98.
- Tol, R.S.J. (1997) On the optimal control of carbon dioxide emissions: an application of FUND *Environmental Modeling and Assessment* 2: 151—163.
- Tol, Richard S.J. (2017). "The Private Benefit of Carbon and its Social Cost," Working Paper Series 0717, Department of Economics, University of Sussex Business School. <https://ideas.repec.org/p/sus/susewp/0717.html>
- UK Department for Energy Security and Net Zero (2022). "Carbon Valuation." GOV.UK, last updated April 4, 2022. <https://www.gov.uk/government/collections/carbon-valuation--2>.
- US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review", EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf accessed February 28, 2024.
- Storm, S (2017) "How the Invisible Hand is Supposed to Adjust the Natural Thermostat: A Guide for the Perplexed." *Science and Engineering Ethics* vol 23: 1307—1331.
- Pielke Jr., Roger (2020) Economic 'normalisation' of disaster losses 1998–2020: a literature review and assessment," *Environmental Hazards*, 2020, pp. 1-19
- Pielke Jr., Roger (2018): Tracking progress on the economic costs of disasters under the indicators of the sustainable development goals, *Environmental Hazards*, DOI: 10.1080/17477891.2018.1540343

- Formetta, Giuseppe and Luc Feyen (2019) Empirical evidence of declining global vulnerability to climate-related hazards. *Global Environmental Change* 57 101920 <https://doi.org/10.1016/j.gloenvcha.2019.05.004>
- Hu, Bin and Ross McKittrick (2015) Climatic Variations and the Market Value of Insurance Firms. *Journal of Insurance Issues* Vol. 39, No. 1, pp. 92-111 <https://www.jstor.org/stable/43741103>
- Blickle, Kristian; Sarah N. Hamerling, and Donald P. Morgan (2021) : How bad are weather disasters for banks?, Staff Reports, No. 990, Federal Reserve Bank of New York, New York, NY <https://www.econstor.eu/bitstream/10419/247913/1/sr990.pdf>
- Lavelle, Marianne (2019) Carbon Tax Plans: How They Compare and Why Oil Giants Support One of Them. *Inside Climate News* March 7, 2019 <https://insideclimatenews.org/news/07032019/carbon-tax-proposals-compare-baker-shultz-exxon-conocophillips-ccl-congress/>
- Dietz, S., J. Rising, T. Stoerk, G. Wagner (2021) Economic impact of tipping points in the climate system. *PNAS* 2021 Vol. 118 No. 34 e2103081118
- Shen, Bo-Wen, Roger A Pielke Sr and Xubin Zeng (2023) The 50th Anniversary of the Metaphorical Butterfly Effect since Lorenz (1972): Multistability, Multiscale Predictability, and Sensitivity in Numerical Models. *Atmosphere* 2023 14(8) <https://doi.org/10.3390/atmos14081279>
- Crawford, John D (1991) Introduction to Bifurcation Theory. *Reviews of Modern Physics* 63(4) October 1991 991—1037.
- Kypke, K. L., Langford, W. F., and Willms, A. R.: Anthropocene climate bifurcation, *Nonlin. Processes Geophys.*, 27, 391–409, <https://doi.org/10.5194/npg-27-391-2020>, 2020.
- Brunetti, Maura and Charline Ragon (2023) Attractors and bifurcation diagrams in complex climate models. *Physical Review E* 107 054214 <https://journals.aps.org/pre/abstract/10.1103/PhysRevE.107.054214>
- Dakos, Vasilis, Chris Boulton, Joshua Buxton et al. (2024) Tipping point detection and early warnings in climate, ecological, and human systems. *Earth System Dynamics* 15 1117—1135 <https://doi.org/10.5194/esd-15-1117-2024>
- Palmer, TN, A Döring and G Seregin (2014) The real butterfly effect. *Nonlinearity* 27(9) 10.1088/0951-7715/27/9/R123 <https://iopscience.iop.org/article/10.1088/0951-7715/27/9/R123/meta>
- Lenton, T.M., D.I. Armstrong McKay, S. Loriani, J.F. Abrams, S.J. Lade, J.F. Donges, M. Milkoreit, T. Powell, S.R. Smith, C. Zimm, J.E. Buxton, E. Bailey, L. Laybourn, A. Ghadiali, J.G. Dyke (eds), 2023, *The Global Tipping Points Report 2023*. University of Exeter, Exeter, UK.

13 U.S. Climate Policy and the Global Climate

Chapter Summary

Because of the pace and scale of the global carbon cycle, US policy actions will only have small effects on the global climate and will only take effect with long delays. Even large reductions in US motor vehicle emissions, for instance, will have effects on global warming well below the threshold of measurability.

13.1 The scale problem

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small - when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves operates on a very different scale, since the effect we are considering is at the global level and the global carbon cycle is vast and slow. A change in local emissions today will have only a very small global effect, and only with a long delay.

After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently, it will take decades or centuries for U.S. CO₂ emission reductions to have a meaningful impact on the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up being too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions have minimal local effects, and only with a long delay. The practice of referring to unilateral US reductions as "combatting climate change" or "taking action on climate" reflects a profound misunderstanding of the scale of the issue.

13.2 Case study: US motor vehicle emissions

The scale problem can be vividly illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if

pollutants are found to endanger public health or welfare. Thus, the 2009 Endangerment Finding obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the US public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing US vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to how much global emissions are reduced, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0% of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating all US vehicle-based emissions would change the multidecadal warming trend by at most 3%. If we were to take into account emissions from land use and cement production, that fraction would be even smaller, but for the purpose of the following calculation, it will suffice.

For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends from five global temperature datasets range from +0.163 deg. C per decade in the NCEP/NCAR R1 reanalysis dataset to +0.211 deg. C per decade in the ERA5 reanalysis dataset. We can take this to be the range of precision with which we can estimate global warming. The latter estimate is 29% larger than the former, indicating that reduction in the rate of global warming from eliminating U.S. vehicle CO₂ emissions would be an order of magnitude below the limits of measurability. Likewise if vehicle emissions were reduced by only, say, 10 percent, the effect on the climate would be two orders of magnitude below the limits of measurement.

Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, due to the nature of the CO₂ issue, and in contrast to the case of local air contaminants like particulates and ozone, even aggressive regulatory actions on GHGs cannot be expected to remediate alleged climate dangers to the US public on any even remotely-measurable scale.

EPA (2024) *Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions 1990-2022*. Available online at <https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P101AKR0.pdf>

Energy Institute (2024) *Statistical Review of World Energy*. Available online at <https://www.energyinst.org/statistical-review>

1 Carbon dioxide as a pollutant

Chapter summary

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Contaminants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

The Clean Air Act of 1970 defined six so-called Criteria Air Contaminants subject to regulation (EPA, undated): particulate matter, ground-level Ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and Carbon Monoxide (CO). In 2006, the Supreme Court ruled that greenhouse gases (CO₂ among them) were also “pollutants” subject to regulation under Clean Air Act (Mass. V. EPA 2006). While the definition of “pollutant” is ultimately a legal one, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are beneficial for vegetation. In these aspects, CO₂ is similar to water vapor.

Ambient outdoor air today contains about 430 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen *et al.* (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG) that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

Massachusetts v. EPA (2006) <https://www.oyez.org/cases/2006/05-1120>

US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and

Conventional Office Environments. *Environmental Health Perspectives* 124(6) pp. 805-812
<https://doi.org/10.1289/ehp.1510037>

2 Direct Impacts of CO₂ on the environment

Chapter summary

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water reduces the alkalinity of the oceans. The recent decline in alkalinity is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Declining alkalinity might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4% and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

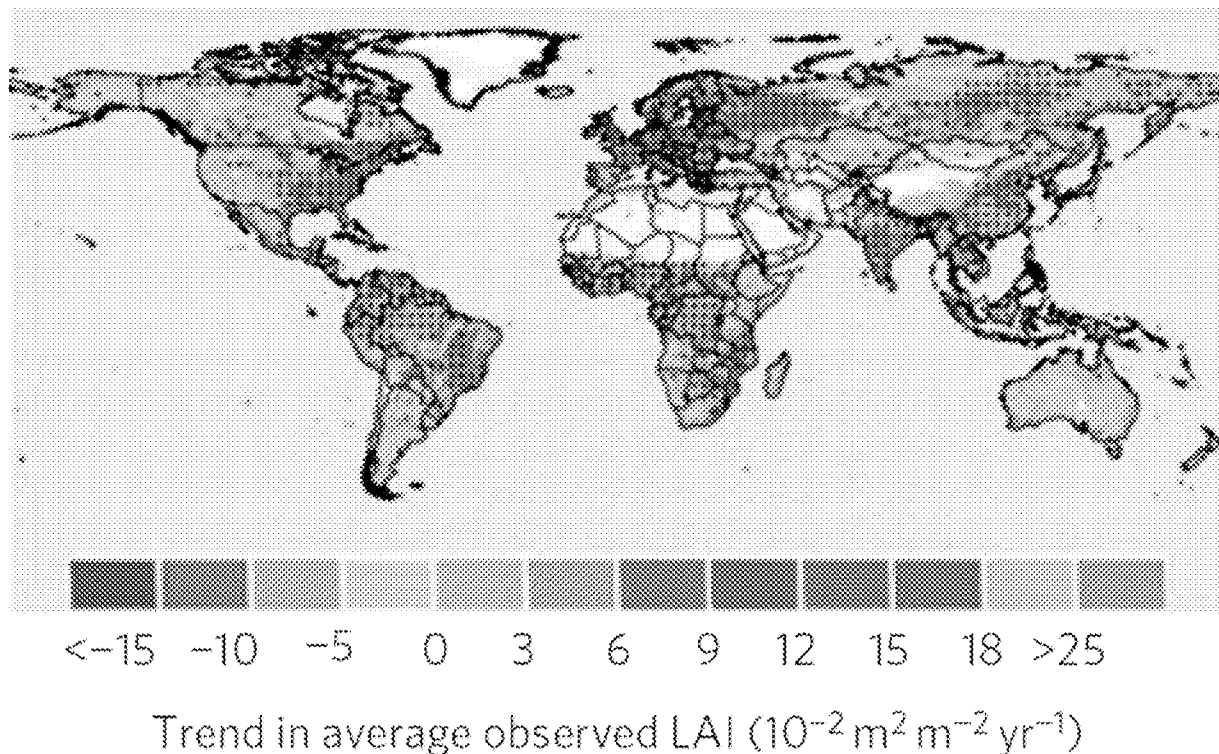


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it through land management changes. Thus, while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increased photosynthesis in response to rising CO_2 , Haverd et al. (2020) reported a CO_2 fertilization rate nearly double what models had predicted. That is, CO_2 fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO_2 have likely understated the benefits to crops and agriculture. The connection between CO_2 fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO_2 fertilization remained the dominant driver.

2.1.2 Photosynthesis and CO_2 levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO_2 is available at the surface

of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

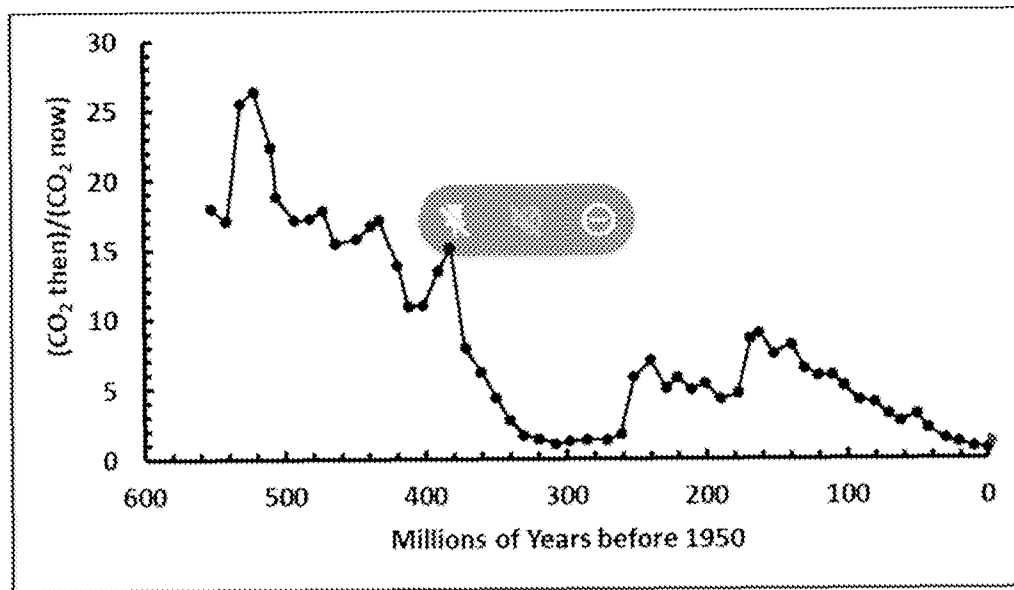


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of “current” levels. Today’s concentration of 420 ppm would plot as 1.4 in the lower right-hand corner of the graph. Source: Berner (2006)

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010).

It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

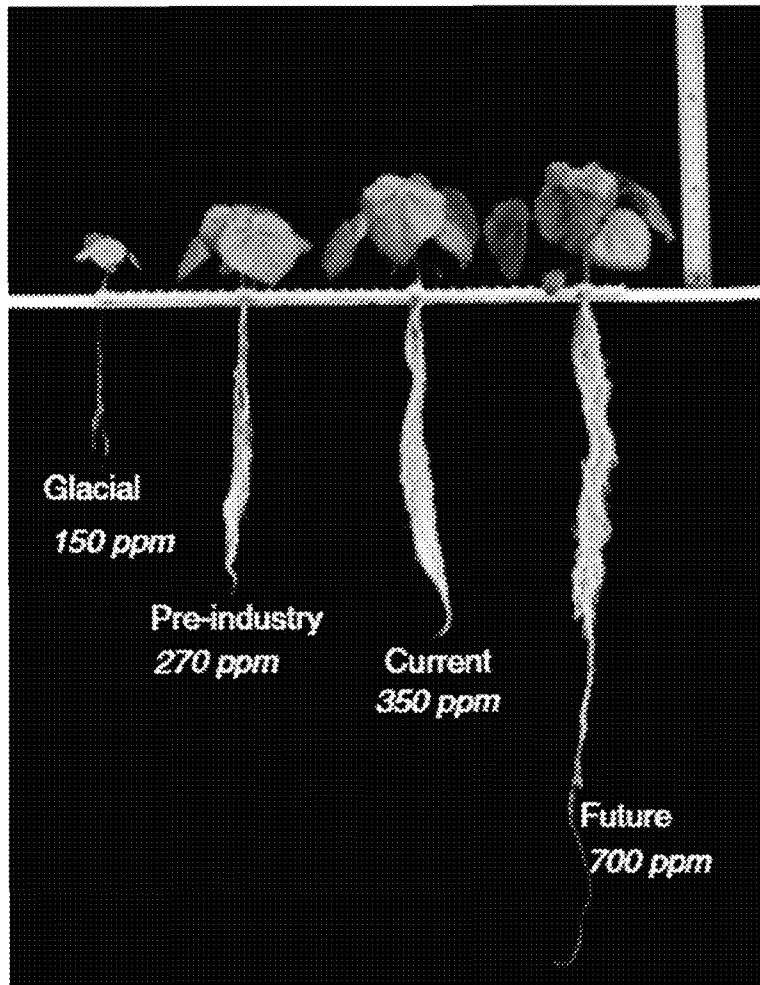


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 CO₂ fertilization benefits in IPCC Reports

The IPCC has only minimally discussed global greening and CO₂ fertilization of agricultural crops. The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the

oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

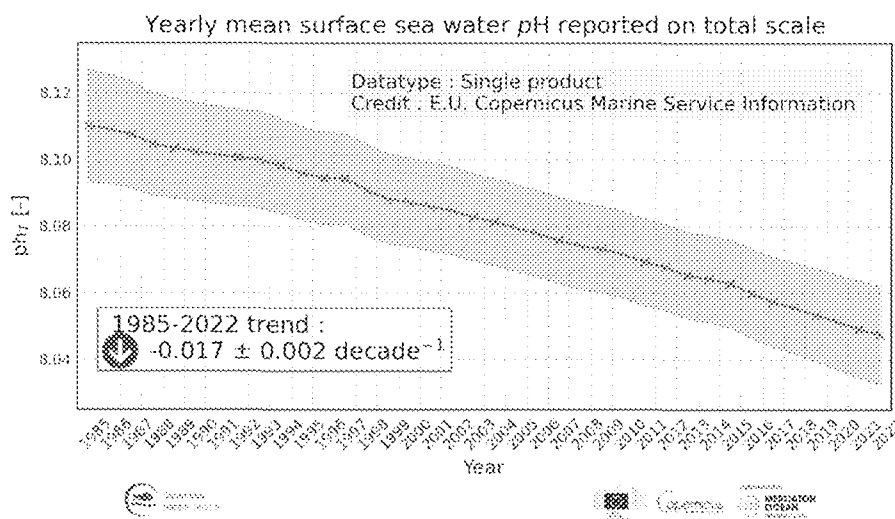


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

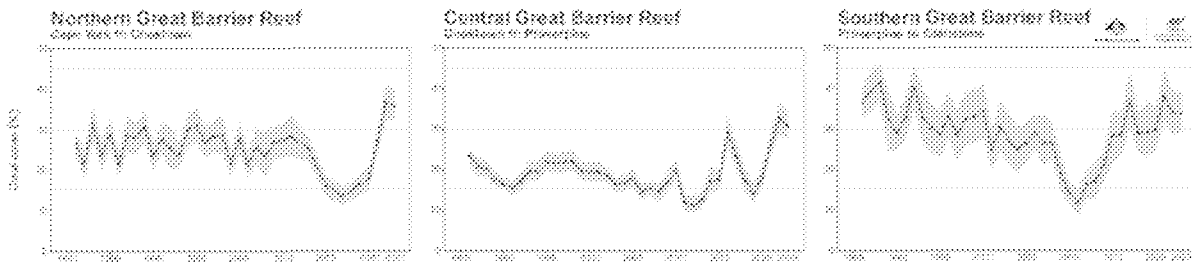


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.
Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

References

Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>

- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.
- Berner, R.A. (2006) GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
- Chen, Xin et al. (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791 <https://www.sciencedirect.com/science/article/pii/S2351989423004262>
- Cheng, L., Zhang, L., Wang, YP. et al. Recent increases in terrestrial carbon uptake at little cost to the water cycle. *Nature Communications* 8, 110 (2017). <https://doi.org/10.1038/s41467-017-00114-5>
- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Climate Change* 18 April 2016 DOI: 10.1038/NCLIMATE2995.
- Gerhart, Laci and Joy Ward (2010) Plant responses to low [CO₂] of the past. *New Phytologist* 188:674—695. <https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>
- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* 26: 2390–2402.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, 764, 142797.
- Judd, Emily et al. (2024) A 485-million-year history of Earth's surface temperature. *Science* 385 Issue 6715 <https://doi.org/10.1126/science.adk3705>
- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, 15(10), e0241081.
- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105-112.
- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, 112, 125961.
- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* 1:14-27
- Verhage, F. Y. (2017, November). Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil. Retrieved October 2024, from esalq: http://www.esalq.usp.br/departamentos/leb/eventos/Thesis_Report_-_Fabian_Verhage.pdf
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* 7:432-436 May 2017 <https://www.nature.com/articles/nclimate3299>
- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 <https://www.nature.com/articles/s43247-024-01463-y>
- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* 6 Aug 2016 <https://www.nature.com/articles/nclimate3004>
- Australian Institute of Marine Science (2022). Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef.

- [https://www.aims.gov.au/sites/default/files/2022-08/AIMS LTMP Report on%20GBR coral status 2021 2022 040822F3.pdf](https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf)
- Beeden, R., Maynard, J., Puotinen, M., Marshall, P., Dryden, J., Goldberg, J., and Williams, G. (2015). Impacts and Recovery from Severe Tropical Cyclone Yasi on the Great Barrier Reef. PLOS ONE. 10. e0121272. <https://doi.org/10.1371/journal.pone.0121272>
- Browman, H. (2016). Applying organized scepticism to ocean acidification research. iCES Journal of Marine Science: Journal du Conseil. 73. 529.1-536. <https://doi.org/10.1093/icesjms/fsw010>
- Clements JC, Sundin J, Clark TD, Jutfelt F (2022) Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. PLoS Biol 20(2): e3001511. <https://doi.org/10.1371/journal.pbio.3001511>
- De'ath, G., Lough, J., and Fabricius, K. (2009). Declining Coral Calcification on the Great Barrier Reef. Science (New York, N.Y.). 323. 116-9. <https://doi.org/10.1126/science.1165283>
- Gattuso, J. P. and Hansson, L. (2011). Ocean acidification: background and history Ocean Acidification ed J P Gattuso and L Hansson (Oxford: Oxford University Press).
- Krissansen-Totton, J., Arney, G., and Catling, D. (2018). Constraining the climate and ocean pH of the early Earth with a geological carbon cycle model. Proceedings of the National Academy of Sciences. 115. 201721296. <https://doi.org/10.1073/pnas.1721296115>
- Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO2 storage and release in the deep Southern Ocean on millennial to centennial timescales. Nature. 562. <https://doi.org/10.1038/s41586-018-0614-0>
- Revelle, R. R. and R. Fairbridge (1957). Carbonate and carbon dioxide, in Treatise on Marine. Ecology and Paleoecology, Vol. 1: J. W. Hedgpeth, ed.
- Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. Marine Geology. 346. 392–399. <https://doi.org/10.1016/j.margeo.2013.09.002>
- Woods Hole Oceanographic Institution (2023). Is the Great Barrier Reef Making a Comeback? <https://www.whoi.edu/oceanus/feature/is-the-great-barrier-reef-making-a-comeback/>
- Copernicus Marine Service (2025) Global Ocean acidification - mean sea water pH time series and trend from Multi-Observations Reprocessing. Online source [https://data.marine.copernicus.eu/product/GLOBAL OMI HEALTH carbon ph area averaged/description](https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description)

3 Human influences on the climate

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth’s energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC’s estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

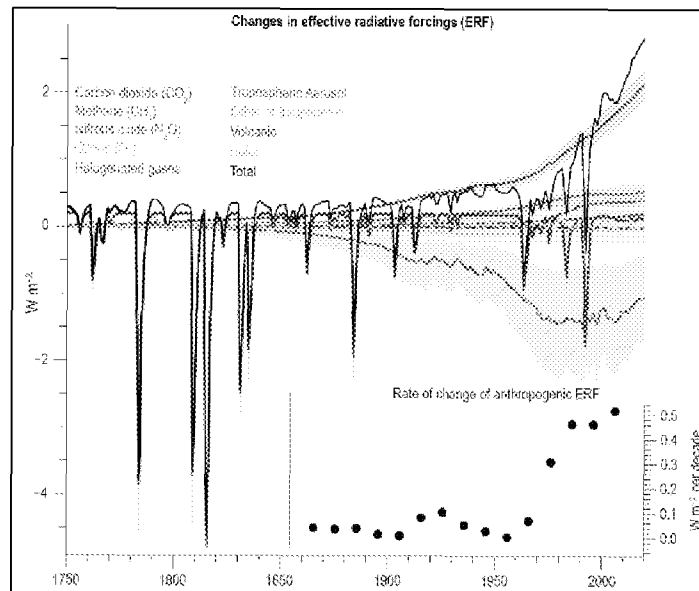


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

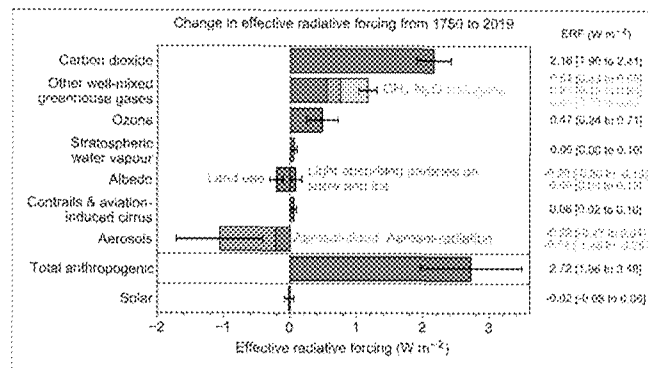


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of energy systems. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO_2 are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO_2 's warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent

warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th Century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the ACRIM data gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global

average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

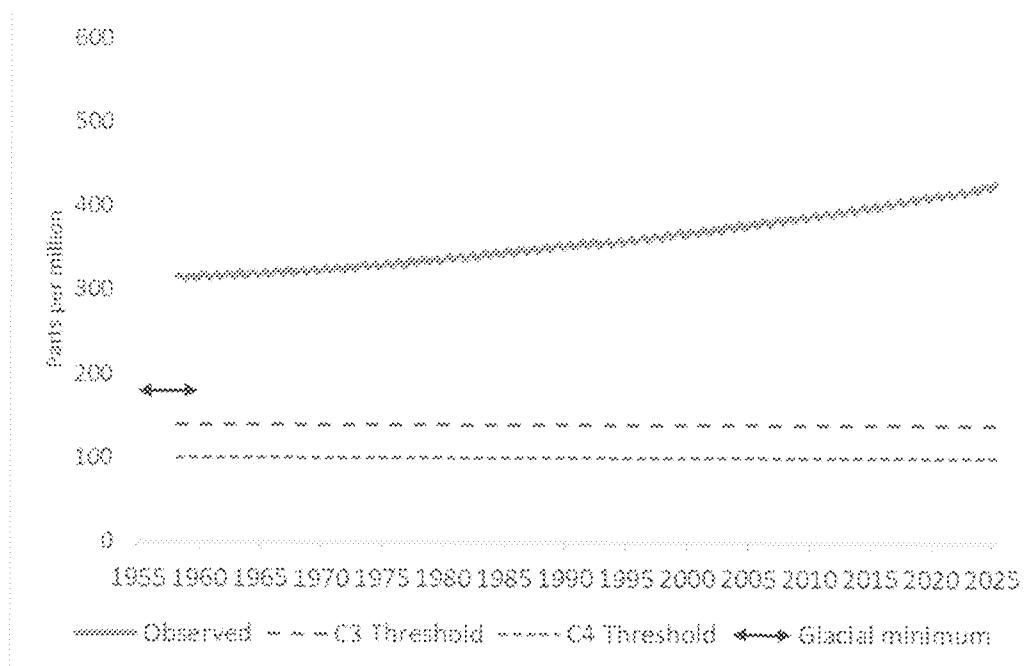


Fig. 4.1.3 CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: <https://gml.noaa.gov/ccgg/trends/index.html>

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If they are not removed the data may over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures suffice for the purpose.

AR6 downplayed the issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10% in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10% upper bound without citing a source. AR4 (WGI p. 244) cited Jones et al. (1990) and Peterson et al. (1999) as the basis of the claim. Peterson et al. had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons and the relative influence of urbanization begins well below that (Spencer et al 2025). Jones et al. compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to 10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10% in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10% of the observed warming trend.

Prior to the IPCC AR4 several papers appeared in print arguing that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. The claim attracted controversy because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. The AR5 (p. 189) conceded that the AR4 had provided “no explicit evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as noted, elsewhere in the report they carried forward the AR4 claim that it was less than 10% of observed warming and they expressed no caution against using the land record for climate measurement on the assumption that it is not contaminated with UHI bias. Recently Soon et al. (2023) estimated an urbanization bias in the Northern Hemisphere land

record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

In summary while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases are not removed by the data processing algorithms used to produce climate data sets. Spencer et al. (2025) propose a new method for measuring UHI biases at local levels using new historical population archives, which may provide a way of further testing for and quantifying the urbanization biases in climate data.

3.3 Future emission scenarios and the carbon cycle

3.3.1 Emission scenarios

Because of the great uncertainties about these many factors in the decades to come, Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

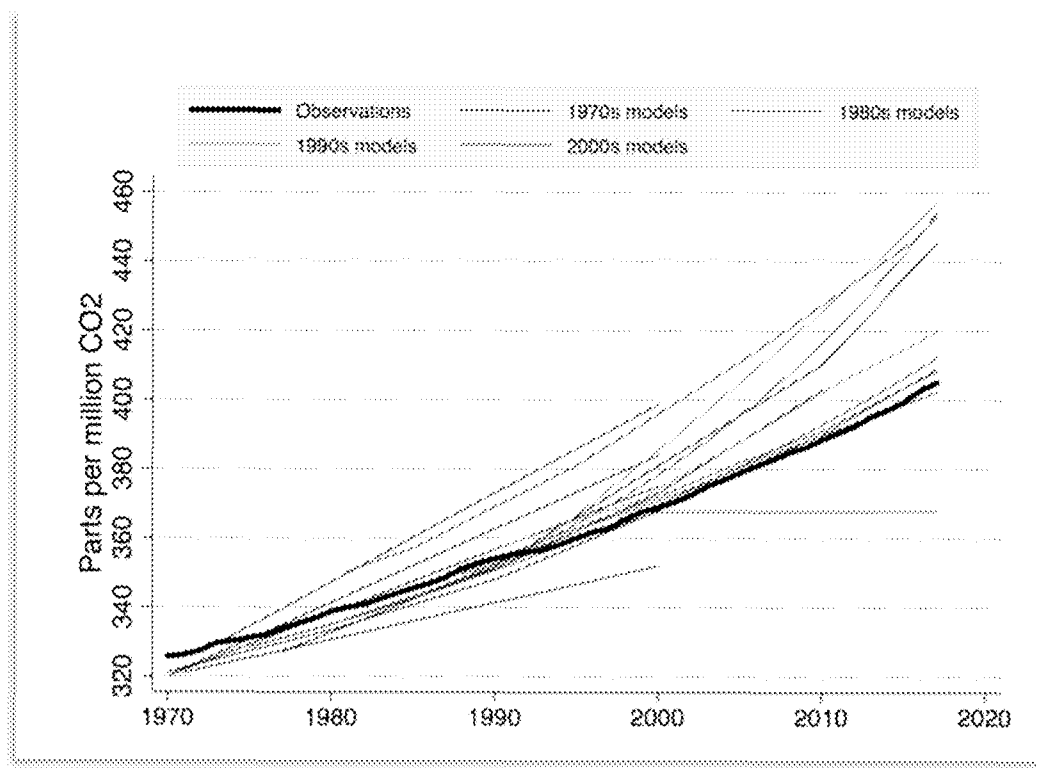


Figure 3.3.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather et al. (2019) Figure S4.

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.3.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

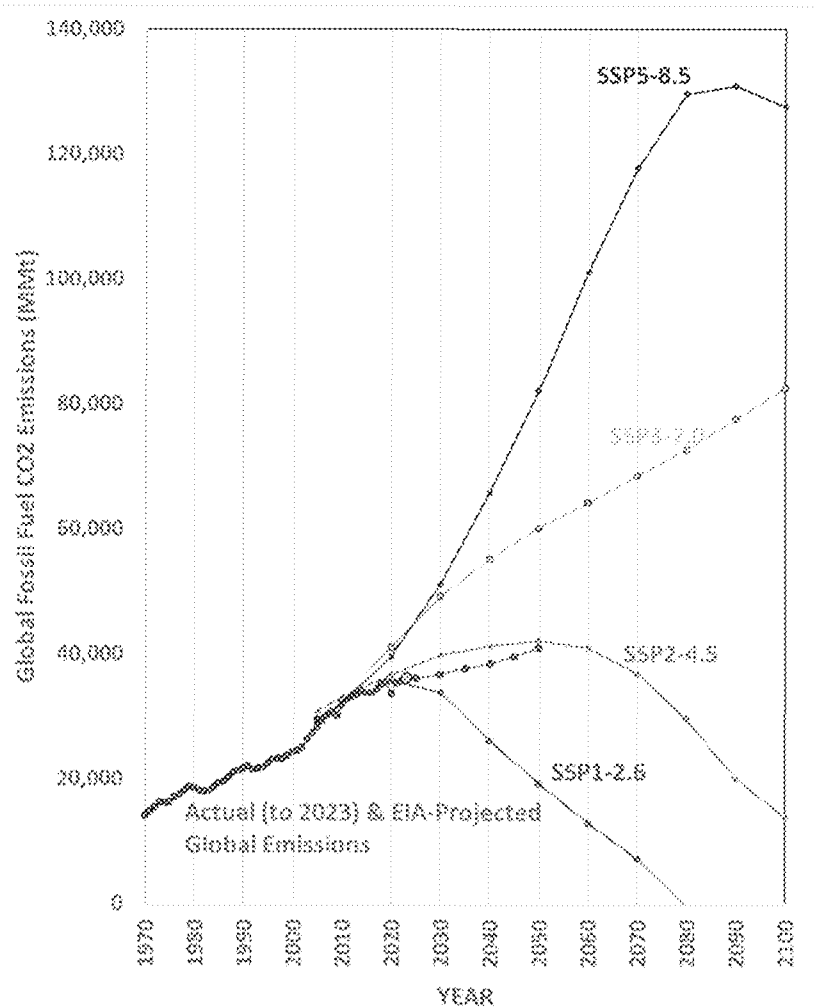


Figure 3.3.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.3.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that exchange CO₂ with the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but the natural CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice

cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The historical near-constancy of that 50% fraction also means that the more CO₂ humanity has produced, the faster Nature removed it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in the 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

[TO BE INSERTED: Land and ocean models vary widely and new information shows processes that are not well understood]

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129, <https://doi.org/10.1029/2024JD041296>

Jones, P. D., P. Y. Groisman, M. Coughlan, N. Plummer, W.-C. Wang, and T. R. Karl (1990), Assessment of urbanization effects in time series of surface air temperature over land, *Nature*, 347, 169 – 172

Peterson, Thomas C., Kevin P. Gallo, Jay Lawrimore, Timothy W. Owen, Alex Huang, David A. McKittrick (1999) Global rural temperature trends. *Geophysical Research Letters* February 1999 <https://doi.org/10.1029/1998GL900322>

De Laat, A.T.J., and A.N. Maurellis (2006), Evidence for influence of anthropogenic surface processes on lower tropospheric and surface temperature trends, *International Journal of Climatology* 26:897—913.

McKittrick, R.R. and P.J. Michaels (2007), Quantifying the influence of anthropogenic surface processes and inhomogeneities on gridded global climate data, *Journal of Geophysical Research*, 112, D24S09, doi:10.1029/2007JD008465.

McKittrick, Ross R. and Nicolas Nierenberg (2010) Socioeconomic Patterns in Climate Data. *Journal of Economic and Social Measurement*, 35(3,4) pp. 149-175. DOI 10.3233/JEM-2010-0336

McKittrick, Ross R. (2010) Atmospheric Oscillations Do Not Explain the Temperature-Industrialization Correlation. *Statistics Politics and Policy* Vol 1. No. 1., July 2010

Spencer, Roy W, John R Christy and William D. Braswell (2025) Urban Heat Island Effects in U.S. Summer Surface Temperature Data, 1895–2023 *Journal of Applied Meteorology and Climatology* April 2025 <https://doi.org/10.1175/JAMC-D-23-0199.1>

Soon,W.; Connolly, R.; Connolly, M.; Akasofu, S.-I.; Baliunas, S.; et al. (2023) The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data. *Climate* 2023, 11, 179. <https://doi.org/10.3390/cli11090179>

3 Human influences on the climate

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. Models disagree over the rate of land and ocean CO₂ absorption but all agree that it has been trending up since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth’s energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms

while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

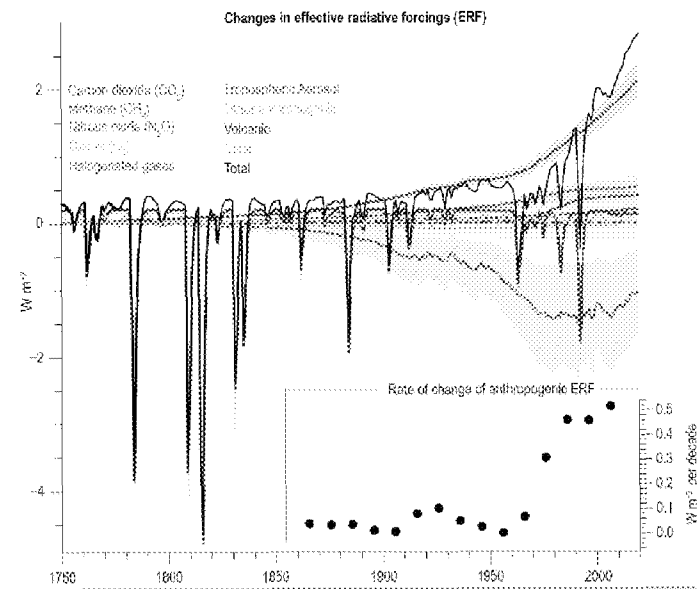


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

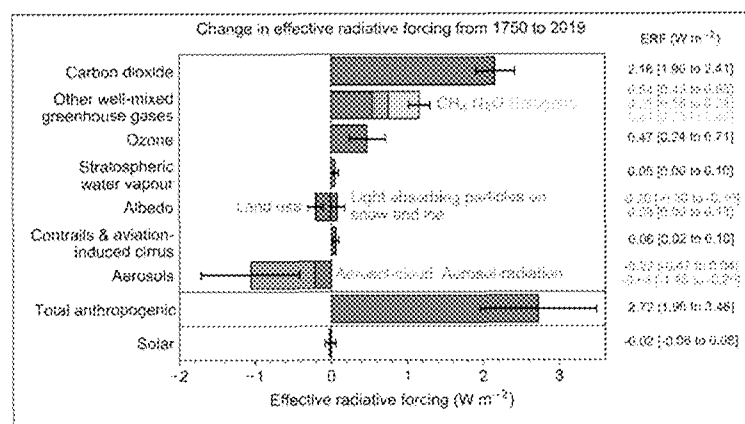


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of energy systems. It exerts a warming influence by decreasing the

cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th Century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the ACRIM data gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

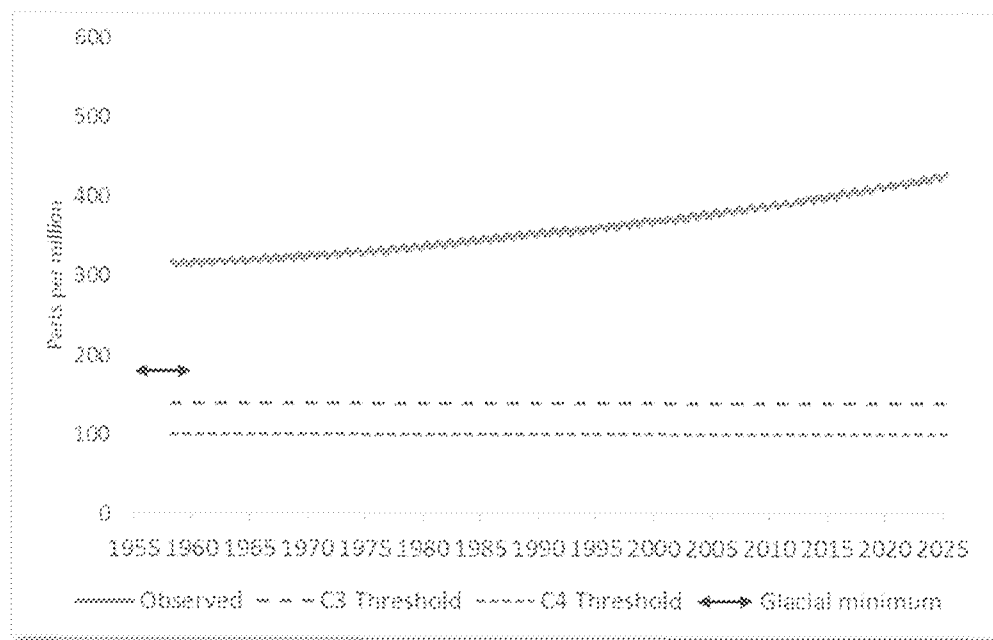


Fig. 3.1.3. CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: <https://gml.noaa.gov/ccgg/trends/index.html>

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If they are not removed the data may over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures suffice for the purpose.

AR6 downplayed the issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10% in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10% upper bound without citing a source. AR4 (WGI p. 244) cited Jones et al. (1990) and Peterson et al. (1999) as the basis of the claim. Peterson et al. had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons and the relative influence of urbanization begins well below that (Spencer et al 2025). Jones et al. compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to 10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10% in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10% of the observed warming trend.

Prior to the IPCC AR4 several papers appeared in print arguing that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. The claim attracted controversy because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. The AR5 (p. 189) conceded that the AR4 had provided “no explicit

evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as noted, elsewhere in the report they carried forward the AR4 claim that it was less than 10% of observed warming and they expressed no caution against using the land record for climate measurement on the assumption that it is not contaminated with UHI bias. Recently Soon et al. (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones et al. 1990, Peterson et al. 1999, Wickham et al. 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic, in other words it is strongest at low population growth levels then tapers off as local urbanization expands (Oke 1973, Spencer et al. 2025). Hence finding the same or more warming in rural areas than in nearby urban areas is consistent either with UHI bias being absent or present. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) instead examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer et al. (2025) use newly-available historical population archives to undertake such an analyses and found evidence of significant UHI bias in US summertime temperature data.

In summary while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases are not removed by the data processing algorithms used to produce climate data sets.

3.3 Future emission scenarios and the carbon cycle

3.3.1 Emission scenarios

Because of the great uncertainties about these many factors in the decades to come, Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

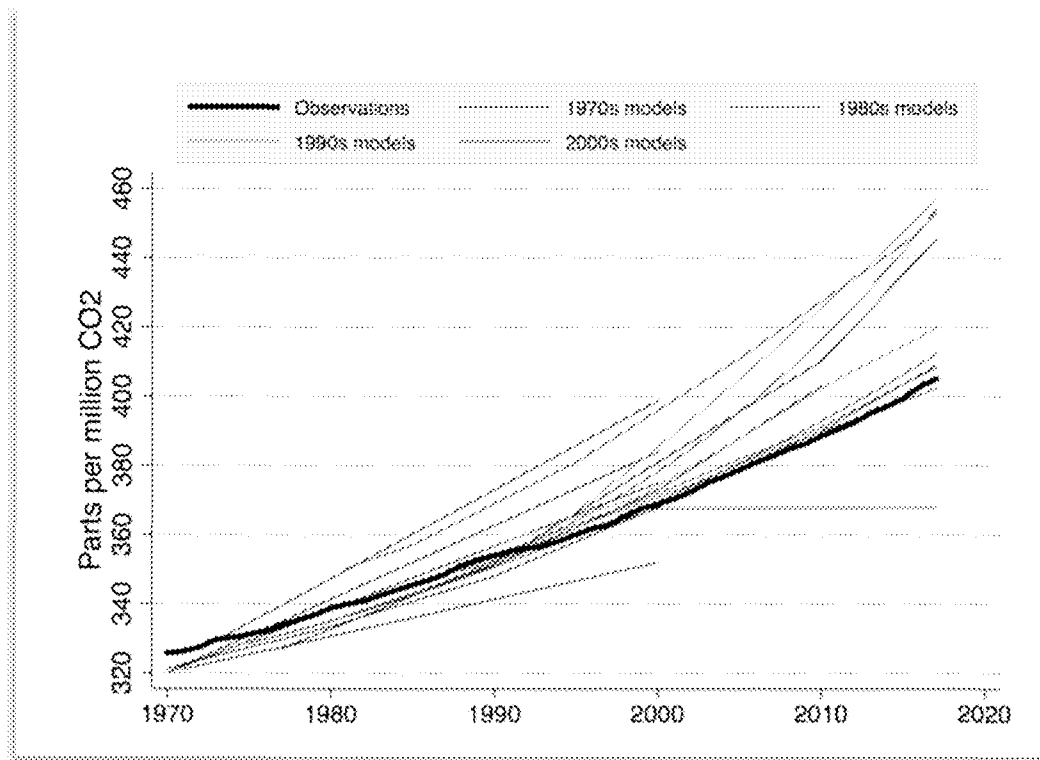


Figure 3.3.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather et al. (2019) Figure S4.

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.3.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) **check source** merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

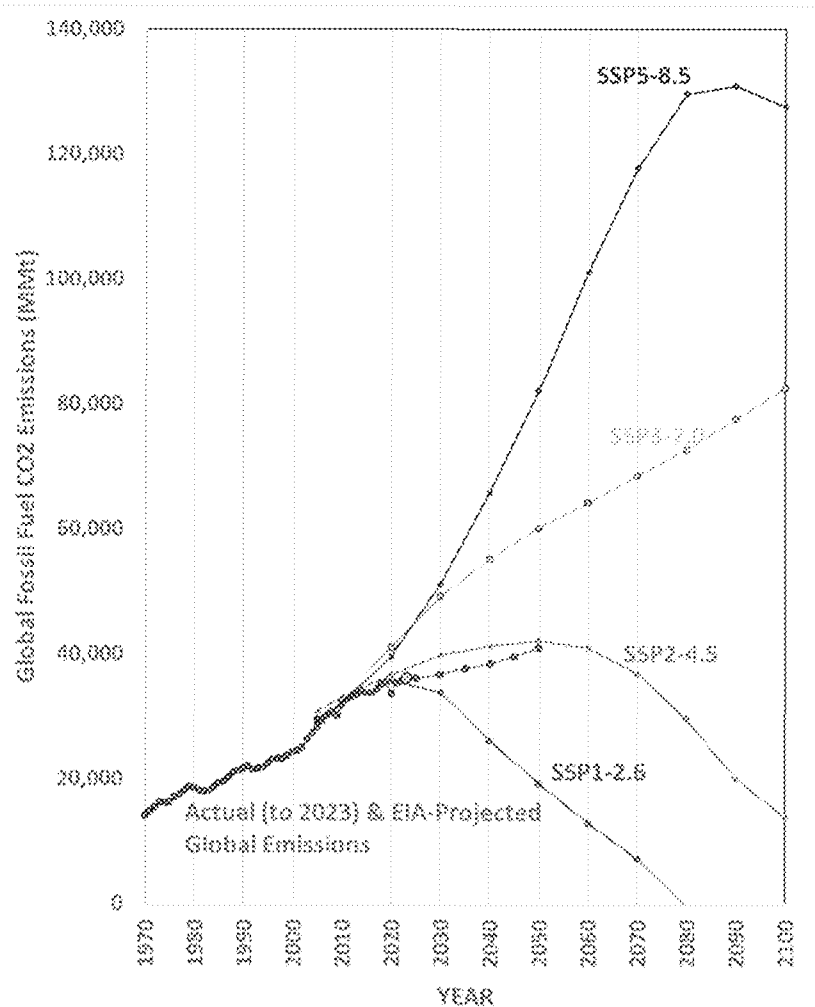


Figure 3.3.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5.

3.3.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that exchange CO₂ with the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but the natural CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice

cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 3.1.3. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The historical near-constancy of that 50% fraction also means that the more CO₂ humanity has produced, the faster Nature removed it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in the 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.3.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty regarding how fast CO₂ from the atmosphere is being removed by land processes, which in turn translates into uncertainty regarding future atmospheric CO₂ concentrations. Those uncertain future CO₂ concentrations then imply a source of uncertainty in climate model simulations of future climate change.

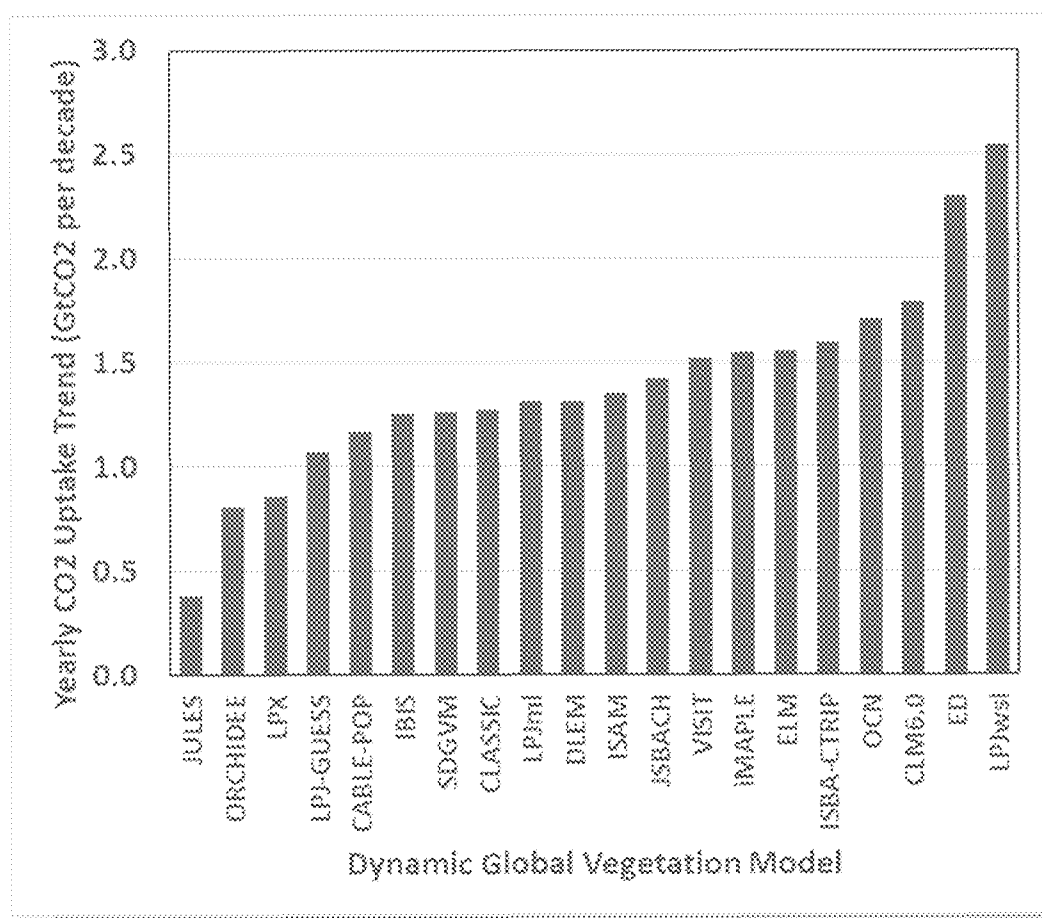


Figure 3.3.3 Decadal trends in the yearly CO₂ uptake by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.3.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake being only 65% faster than the model with the most slowly increasing CO₂ uptake. Note that the average trend in CO₂ uptake across all land models in Fig. 3.3.3 is 25% larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

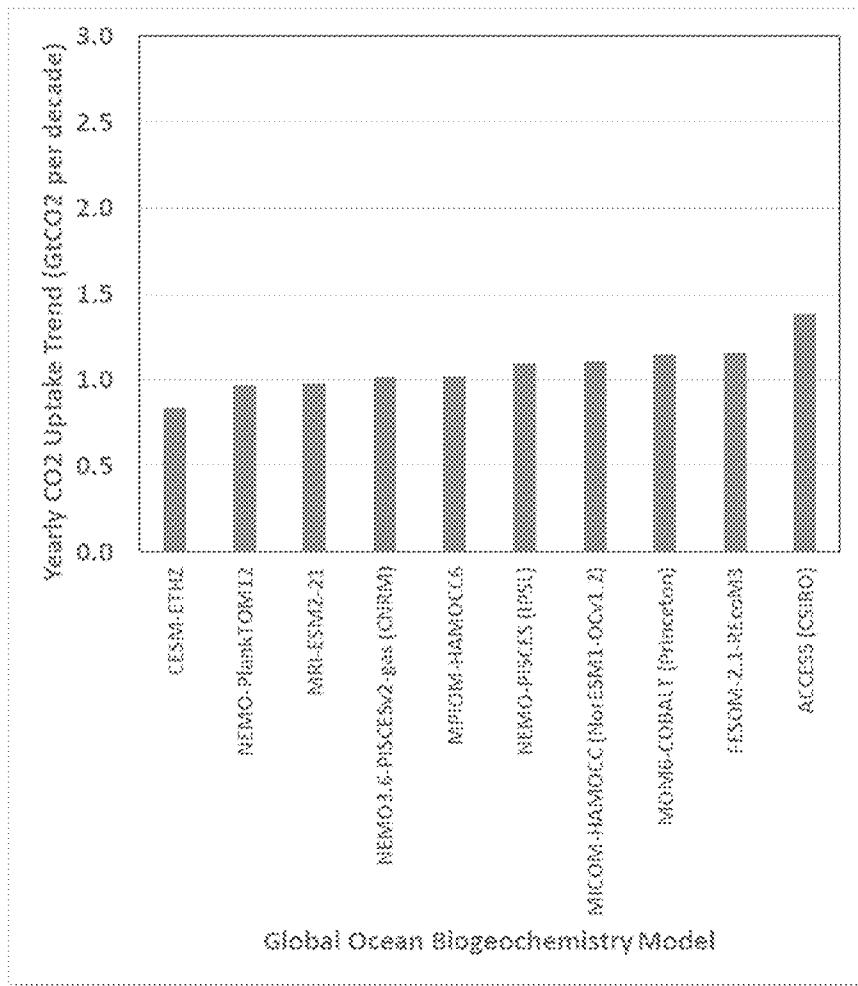


Figure 3.3.5 Decadal trends in the yearly CO₂ uptake by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. *Nat. Clim. Chang.* 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. *J. Geophys. Res.*, 129,

<https://doi.org/10.1029/2024JD041296>

Jones, P. D., P. Y. Groisman, M. Coughlan, N. Plummer, W.-C. Wang, and T. R. Karl (1990), Assessment of urbanization effects in time series of surface air temperature over land, *Nature*, 347, 169 – 172

Peterson, Thomas C., Kevin P. Gallo, Jay Lawrimore, Timothy W. Owen, Alex Huang, David A. McKittrick (1999) Global rural temperature trends. *Geophysical Research Letters* February 1999 <https://doi.org/10.1029/1998GL900322>

De Laat, A.T.J., and A.N. Maurellis (2006), Evidence for influence of anthropogenic surface processes on lower tropospheric and surface temperature trends, *International Journal of Climatology* 26:897—913.

McKittrick, R.R. and P.J. Michaels (2007), Quantifying the influence of anthropogenic surface processes and inhomogeneities on gridded global climate data, *Journal of Geophysical Research*, 112, D24S09, doi:10.1029/2007JD008465.

McKittrick, Ross R. and Nicolas Nierenberg (2010) *Socioeconomic Patterns in Climate Data. Journal of Economic and Social Measurement*, 35(3,4) pp. 149-175. DOI 10.3233/JEM-2010-0336

McKittrick, Ross R. (2010) *Atmospheric Oscillations Do Not Explain the Temperature-Industrialization Correlation. Statistics Politics and Policy* Vol 1. No. 1., July 2010

Spencer, Roy W, John R Christy and William D. Braswell (2025) Urban Heat Island Effects in U.S. Summer Surface Temperature Data, 1895–2023 *Journal of Applied Meteorology and Climatology* April 2025 <https://doi.org/10.1175/JAMC-D-23-0199.1>

Soon, W.; Connolly, R.; Connolly, M.; Akasofu, S.-I.; Baliunas, S.; et al. (2023) The Detection and Attribution of Northern Hemisphere Land Surface Warming (1850–2018) in Terms of Human and Natural Factors: Challenges of Inadequate Data. *Climate* 2023, 11, 179. <https://doi.org/10.3390/cli11090179>

Friedlingstein, P., and 95 co-authors (2024): Global Carbon Budget 2024, *Earth Syst. Sci. Data*, <https://essd.copernicus.org/preprints/essd-2024-519>, 2024

Parker, D.E. (2006) “A Demonstration that Large-Scale Warming is not Urban.” *Journal of Climate* 19:2882—2895.

Oke, T.R., 1973: City size and the urban heat island, *Atmospheric Environment* 7, 769-779

McKittrick, Ross R. (2013) Encompassing Tests of Socioeconomic Signals in Surface Climate Data. *Climatic Change* doi 10.1007/s10584-013-0793-5. Volume 120, Issue 1-2. <http://link.springer.com/article/10.1007%2Fs10584-013-0793-5>

Wickham C, R Rohde, RA Muller, J Wurtele, J Curry, et al. (2013) Influence of Urban Heating on the Global Temperature Land Average using Rural Sites Identified from MODIS Classifications. *Geoinformatics and Geostatistics: An Overview* 1:2.

4 Climate Sensitivity to CO₂ Forcing

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney *et al.* 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5 -- 4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0 - 5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC

changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. Historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 5.1). Far from settling the model-based sensitivity of climate system uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

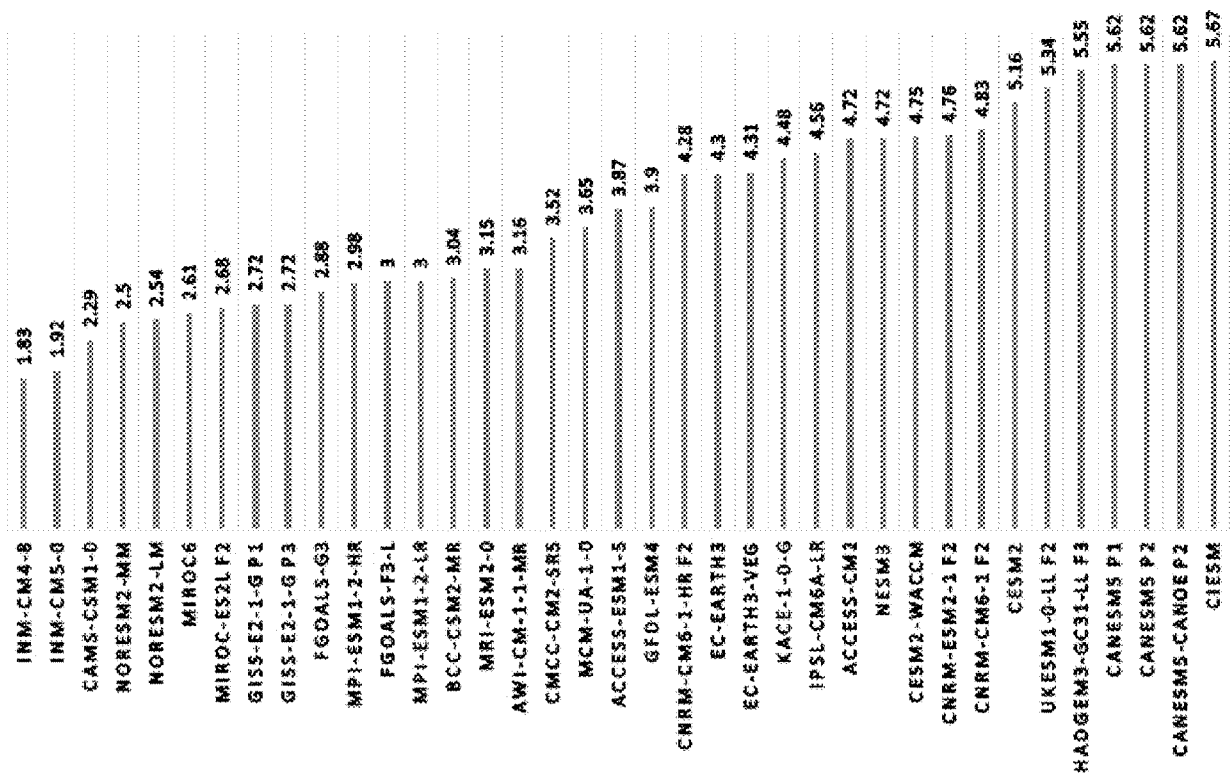


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods, chiefly a recent empirical estimate.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects

need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1

percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems* 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

1. Lan, X., Tans, P. and K.W. Thoning: Trends in globally-averaged CO₂ determined from NOAA Global Monitoring Laboratory measurements. Version Monday, 14-Apr-2025 09:08:57 MDT <https://doi.org/10.15138/9N0H-ZH07>.
2. Zeke Hausfather, "Explainer: How Scientists Estimate Climate Sensitivity," *Carbon Brief*, July 22, 2020, <https://www.carbonbrief.org/explainer-how-scientists-estimate-climate-sensitivity>.
3. Jule Charney et al., "Carbon Dioxide and Climate: A Scientific Assessment," 1979, <https://doi.org/10.17226/12181>.
4. Rajendra K. Pachauri and Leo Meyer, *Climate Change 2014: Synthesis Report* (Geneva, CH: Intergovernmental panel on climate change, 2015).
5. "In-Depth Q&A: The IPCC's Sixth Assessment Report on Climate Science," Carbon Brief, August 9, 2021, <https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-report-on-climate-science>.
6. Nicola Scafetta, "Testing the CMIP6 GCM Simulations versus Surface Temperature Records from 1980–1990 to 2011–2021: High ECS Is Not Supported," *Climate* 9, no. 11 (2021): 161, <https://doi.org/10.3390/cli9110161>.
7. Brian J. Soden and Isaac M. Held, "An Assessment of Climate Feedbacks in Coupled Ocean–Atmosphere Models," *Journal of Climate* 19, no. 14 (July 15, 2006): 3354–3360, <https://doi.org/10.1175/jcli3799.1>.
8. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence," *Reviews of Geophysics* 58, no. 4 (July 22, 2020), <https://doi.org/10.1029/2019rg000678>.

9. Judith A. Curry and Peter J. Webster, "Thermodynamic Feedbacks in the Climate System," in *Thermodynamics of Atmospheres and Oceans* (New York, NY: Academic Press, 1999), 351-385.
10. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
11. D. Chen et al., "Framing, Context, and Methods."
12. Mark D. Zelinka et al., "Causes of Higher Climate Sensitivity in CMIP6 Models," *Geophysical Research Letters* 47, no. 1 (2020): e2019GL085782, <https://doi.org/10.1029/2019GL085782>.
13. Thorsten Mauritsen and Johann Jungclauss, "Tuning the MPI-ESM1.2 Global Climate Model to Improve the Match With Instrumental Record Warming by Lowering Its Climate Sensitivity," *Journal of Advances in Modeling Earth Systems* 12, no. 7 (2020): e2019MS002037, <https://doi.org/10.1029/2019MS002037>.
14. Alexander Otto et al., "Energy Budget Constraints on Climate Response," *Nature Geoscience* 6, no. 6 (May 19, 2013): 415-416, <https://doi.org/10.1038/ngeo1836>.
15. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?" *Atmospheric Chemistry and Physics* 24, no. 5 (2024): 2679–2686, <https://doi.org/10.5194/acp-24-2679-2024>.
16. "Why Low-End 'Climate Sensitivity' Can Now Be Ruled Out," Carbon Brief, July 22, 2020, <https://www.carbonbrief.org/guest-post-why-low-end-climate-sensitivity-can-now-be-ruled-out>.
17. S. C. Sherwood et al., "An Assessment of Earth's Climate Sensitivity."
18. D. Chen et al., "Framing, Context, and Methods."
19. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence," *Climate Dynamics* 61, no. 9–10 (2023): 3155–3163, <https://doi.org/10.1007/s00382-022-06398-8>.
20. Ibid.
21. Steven C. Sherwood and Chris E. Forest, "Opinion: Can Uncertainty in Climate Sensitivity Be Narrowed Further?"
22. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)," *EGUsphere* [preprint], 2025, <https://doi.org/10.5194/egusphere-2025-1179>.
23. P. Forster et al., (2021): The Earth's energy budget, climate feedbacks, and climate sensitivity. In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V. et al. (eds.)], Cambridge University Press, 2021.
24. Richard Seager et al., "Strengthening Tropical Pacific Zonal Sea Surface Temperature Gradient Consistent with Rising Greenhouse Gases," *Nature Climate Change* 9, no. 7 (2019): 517–522, <https://doi.org/10.1038/s41558-019-0505-x>.
25. Sangyeop Lee et al., "Zonal Contrasts of the Tropical Pacific Climate Predicted by a Global Constraint," *Climate Dynamics* 62, no. 1–2 (2024): 229–246, <https://doi.org/10.1007/s00382-023-06741-7>.
26. D. Chen et al., "Framing, Context, and Methods."
27. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
28. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.

29. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
30. Nicholas Lewis, "Comment on 'Can Uncertainty in Climate Sensitivity Be Narrowed Further?' by Sherwood and Forest (2024)."

Nierenberg, William et al. (1983) *Changing Climate: Report of the Carbon Dioxide Assessment Committee*. Washington, National Academies Press 1983.

5 Models versus Observations in the Recent Past

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past few decades. In response to observed changes in forcing inputs they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The IPCC has acknowledged some of these issues but not all.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. To assess the fitness of climate models for this purpose, it is reasonable to ask how well they reproduce the current climate and its variations over the past century. The nearby box “Climate modeling” gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, as we discussed in the previous chapter. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

Box: Climate modeling

All but the simplest computer models of the climate begin by covering the earth’s land surface with a grid of squares, typically 100 km on a side. To describe the atmosphere, 10-20 layers of grid boxes are stacked above those squares. With a similar, but finer, grid covering the ocean, the model comprises one million grid boxes for the atmosphere and 100 million grid boxes for the ocean.

The computer models, based on physical laws, calculate how the air, water, and energy in each box at a given time move to neighboring grid boxes at a slightly later time; this time step can be as small as 10 minutes. Repeating this process millions of times simulates the climate for centuries, a calculation that can take months of computer time on even the most powerful supercomputers. Comparing the results of computer runs with what we know about past climates gives some sense of how good a model is. Calculations into the future under assumed human and natural influences then purport to describe the climate decades hence.

Unfortunately, while all this might sound straightforward, it isn't. A major problem is that many important phenomena are much smaller than the 100 km grid size. For example, flows of sunlight and heat through the atmosphere are influenced by clouds. Because there are far too many clouds to follow each in detail, researchers must make "subgrid" assumptions about the number and type of clouds in each grid box to build a complete model. Cloud cover is only one among dozens of subgrid assumptions. Another is *How much snow or ice is on the surface?*, which controls the heating effect of sunlight.

Each subgrid assumption has numerical parameters that must be set, somehow. Modelers determine subgrid parameters based on what they know about physics and weather and climate observations and then run the model. Since the results generally don't much look like the climate system we observe, modelers adjust ("tune") these parameters to better match some features of the real climate system. Different modelers will make different assumptions with different tunings and so produce widely different results. Tuning is a necessary, but perilous, part of modeling the climate, as it is in modeling of any complex system. An ill-tuned model will be a poor description of the real world, while overtuning risks cooking the books— that is, predetermining the answer.

To extract useful information from vastly different models, results are usually quoted as averages over a collection ("ensemble") of models; the most recent UN IPCC assessments used the CMIP6 ensemble. The diversity of that ensemble is already evident in one of the simplest descriptions of the climate – the earth's average surface temperature. It varies across the ensemble by about 3°C, three times greater than the observed warming during the 20th century.

While it would be reassuring if the models were able to accurately describe the current climate, the crucial issue for society is how well they describe the *response* of the climate to physically small human influences such as warming greenhouse gases, cooling aerosols, and changes in land use. Here, the most important thing that a model has to get right are "feedbacks." Here's how feedbacks work. The growing greenhouse gas concentrations that raise the global temperature can also cause other changes in the climate system that either amplify or suppress their direct warming influence. For example, as the globe gets warmer, there'll be less snow and ice on the surface, which decreases the planet's reflectivity. The less reflective earth will then absorb more sunlight, causing even more warming. Other important feedbacks involve the amount of water vapor and clouds in the atmosphere or the temperature profile of the atmosphere. The average of results over the many different models in the ensembles suggests that the net effect of all feedbacks is to double or triple CO₂'s direct warming influence.

End BOX

5.2 Surface warming

A straightforward test of a climate model's validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 5.2 is reproduced from Scaffeta (2023), a peer-reviewed study that groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

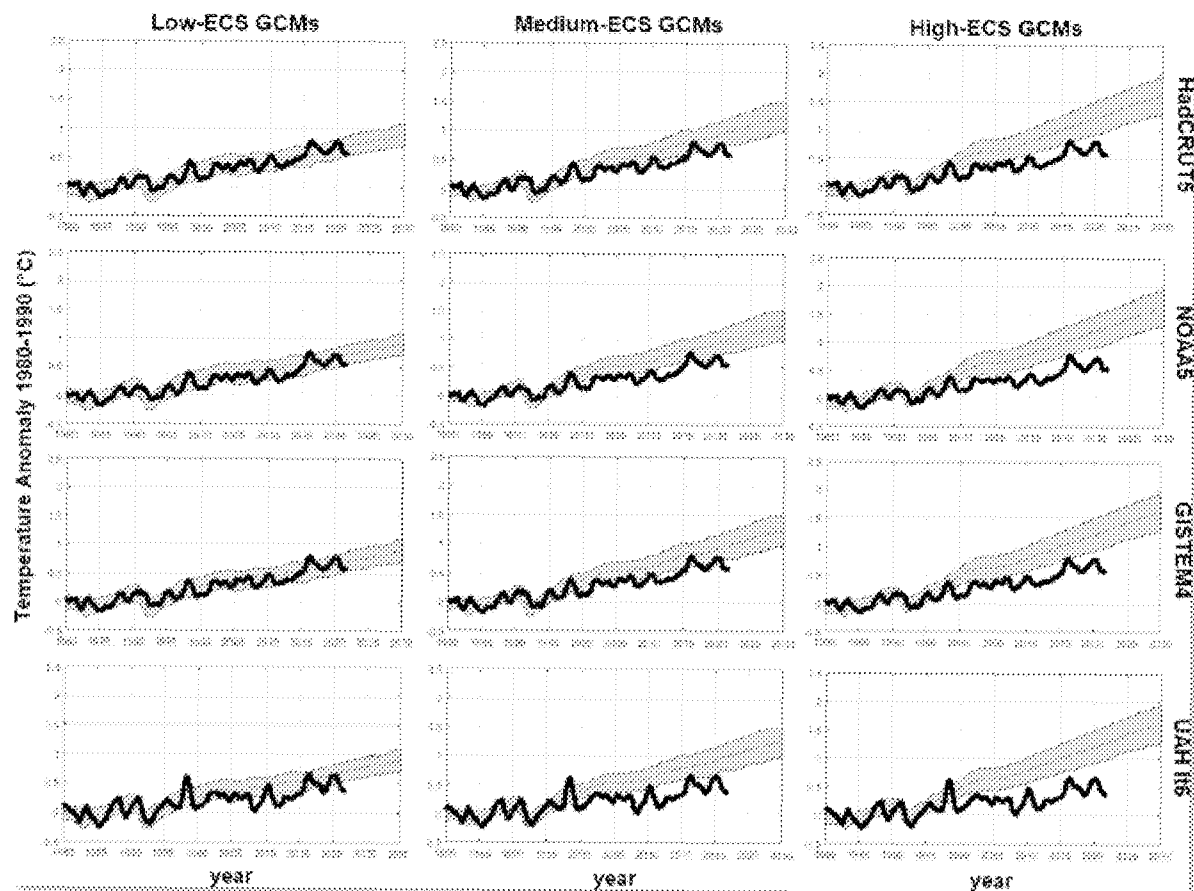


Figure 5.2: model-observational comparisons for Earth’s surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

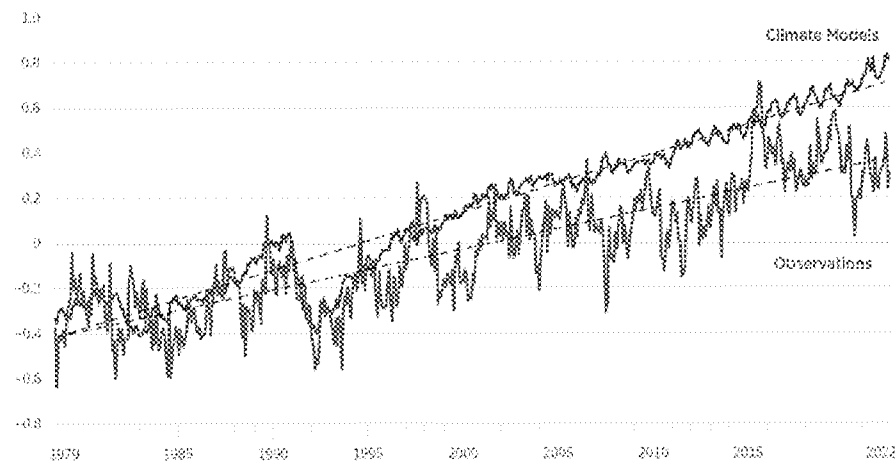
Source: Scafetta N. Climate Dynamics 2023 Fig.2.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by comparing average surface temperature data products with the average climate model warming, as summarized in Figure 5.3.

CHART 1

Global Average Surface-Air Temperature Variations, 1979–2022

DEPARTURE FROM 1981–2010 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Author's calculations based on data from five different observation-based datasets and 36 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and NOAA Climate Explorer, "Starting Point," <https://climateexplorer.noaa.gov/starting-point> (accessed January 10, 2024).

Figure 5.3: Models versus observations at the surface. Source: Spencer (2024) to be updated

5.4 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. This region is an important test of the models since it has long been hypothesized that this is where the signal of anthropogenic greenhouse warming emerges first and most strongly. Biases in tropospheric trends indicate model flaws in heat transfer processes and carry over to surface warming biases.

The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 5.4). Every model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 5.5).

In most individual models the bias is statistically significant and on average across models it is highly significant (Figure 5.4). McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If future climate models were to realistically represent global tropospheric warming, they would likely be less sensitive than even the low-ECS members of the CMIP6 ensemble

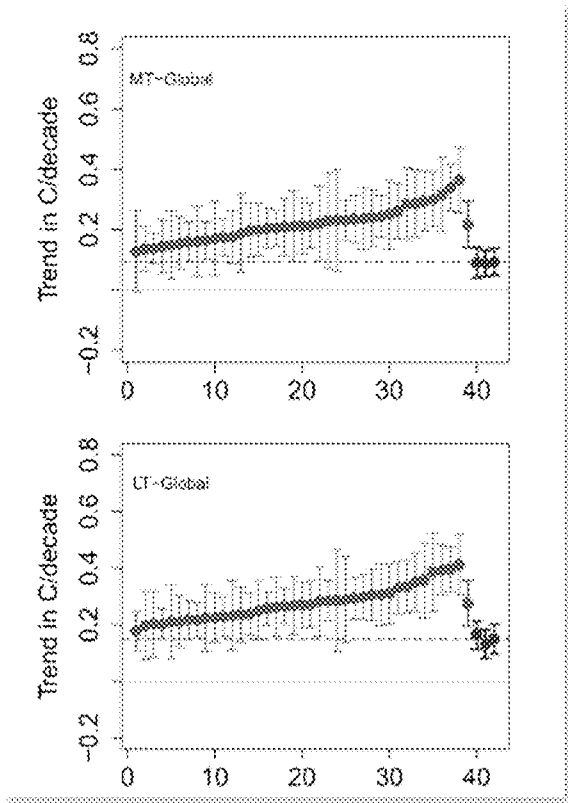


Figure 5.4: Modeled versus observed warming trends in the global lower (LT) and mid-troposphere (MT). Adapted from McKittrick and Christy (2020). Red dots: warming trends ($^{\circ}\text{C}/\text{decade}$) with 95% confidence interval bars for 36 climate models. Blue dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars. Dashed line: model warming trend average.

Spencer (2024) shows the mismatch is also present in the lower troposphere (Figure 5.5).

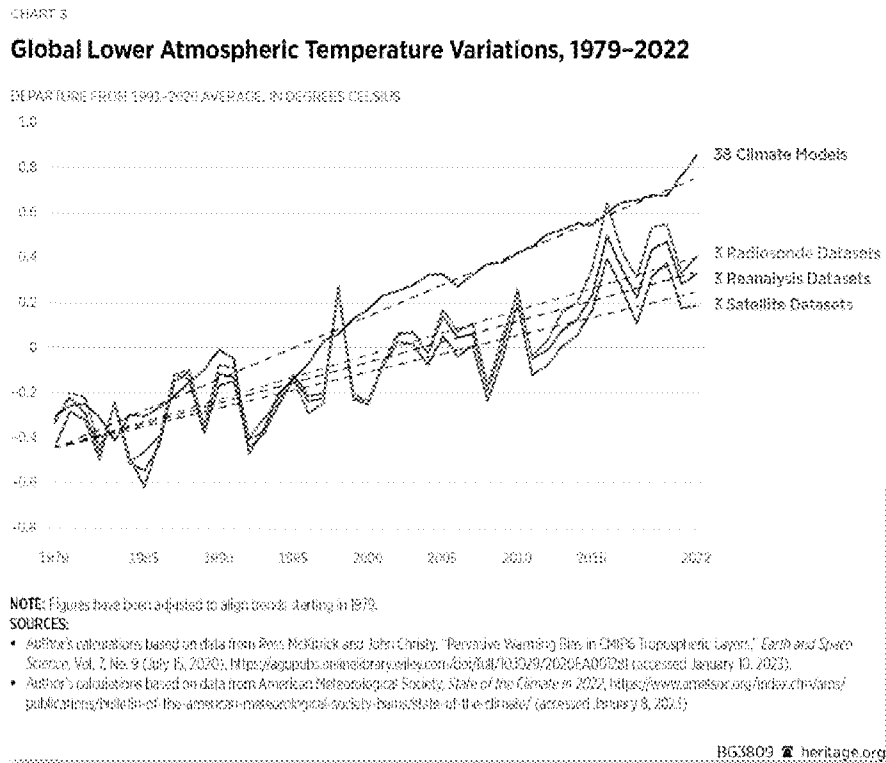


Figure 5.5: Comparison of average trends in lower troposphere, 1979–2022. Source: Spencer (2024). TO BE UPDATED

As mentioned the IPCC has long acknowledged the model-observation mismatch. For example AR6 pp. 443–444 offers this on the tropical troposphere (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5

and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, despite the accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias.

5.5 Vertical profile mismatch and excess amplification

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. The comparison was in the IPCC AR5 Chapter 10, although only in the online supplement (Figure 10.SM.1) and only in a figure the formatting of which made the point difficult to see. Figure 10.SM.1 is not referenced in the main IPCC report nor in any summary so readers would not have been aware of it. Although not apparent at first glance, it shows that the 1979-2010 warming in the lower troposphere is so small as to be consistent with no GHG forcing at all, and is inconsistent with the model runs that do have GHG forcing. In Figure 5.6 we adapt IPCC AR5 Figure 10.SM.1 to draw out the critical point.

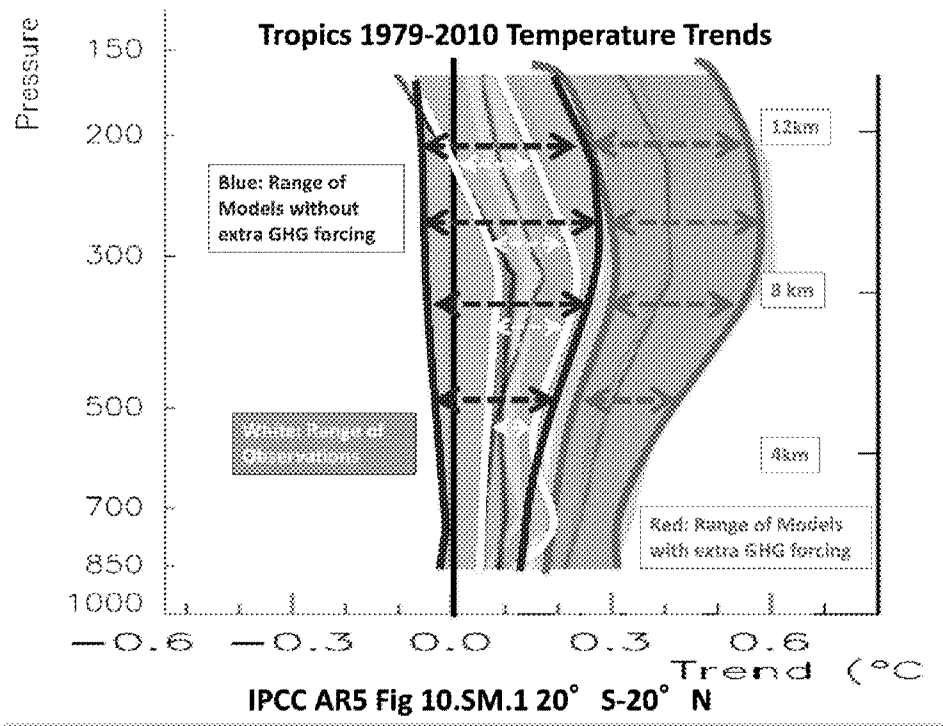


Figure 5.6: Vertical warming pattern for tropics (20S to 20N). Source: Annotated version of IPCC AR5 Figure 10.SM.1

Figure 5.6 compares temperature trends by altitude between models and observations between 20S and 20N (the tropics). In this region where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO2” band and entirely outside the “with CO2” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that*

have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.7. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.7 is the tropical tropospheric temperature (TTT) average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

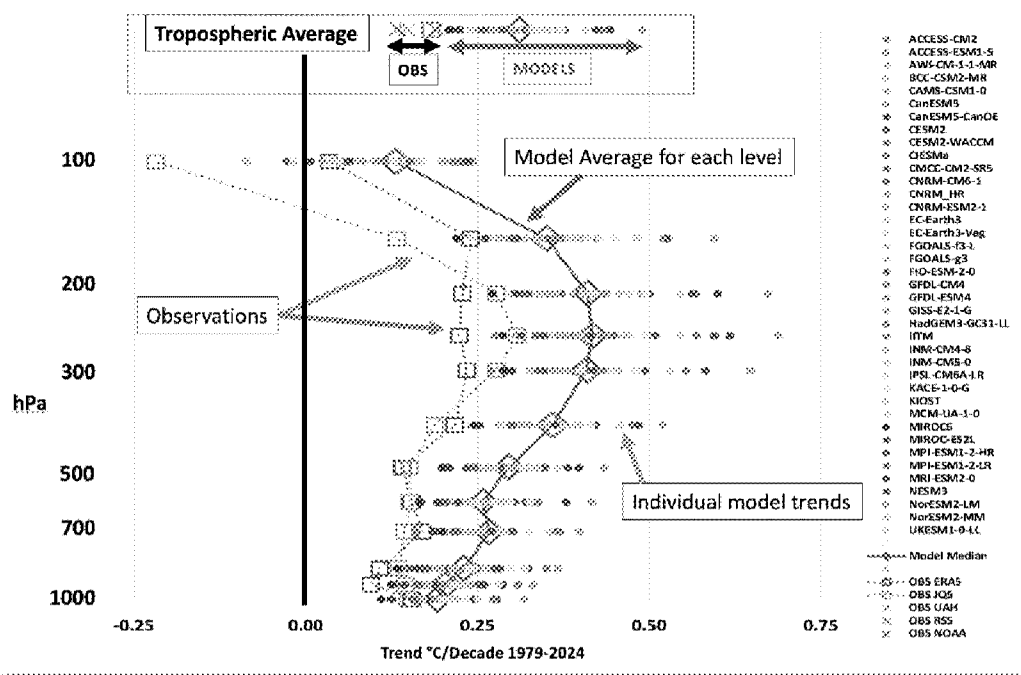


Figure 5.7: Modeled versus observed warming, tropical troposphere. Source: updated from Christy and McNider (2017) including data through 2024. Red line: model average. Green and blue lines: observational series (reanalysis).

This discrepancy has been the source of much controversy, with some arguing that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), showed that models project greater amplification with altitude than is observed. This result was subsequently confirmed by detailed time series analysis (Vogelsang and Nawaz 2016) who found that the model-observational difference is statistically significant.

This is a case in which models are not merely uncertain but share a common bias compared to observations. This suggests the representation of certain fundamental physical processes in climate model feedbacks have large discrepancies not only among models but against the real climate.

The IPCC AR6 did not assess this issue.

5.6 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to the year 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with **the bulk of the decrease prior to 2000**. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate **models project continued tropospheric warming and stratospheric cooling** over the coming decades. Global average satellite observations of **lower stratospheric temperatures exhibit no significant trends since the turn of the century**. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated **radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.**”

A combination of tropospheric warming and stratospheric cooling is a commonly-cited “fingerprint” of anthropogenic warming. Stratospheric warming since 2000 coincides with continued surface and tropospheric warming, a pattern that is not found in climate model simulations and is not apparently consistent with the anthropogenic fingerprint.

5.7 Snow cover mismatch

Data compiled by the Rutgers University Snow Lab (undated) show that Northern Hemisphere winter snow cover is not decreasing. If anything, shows an increasing trend.:

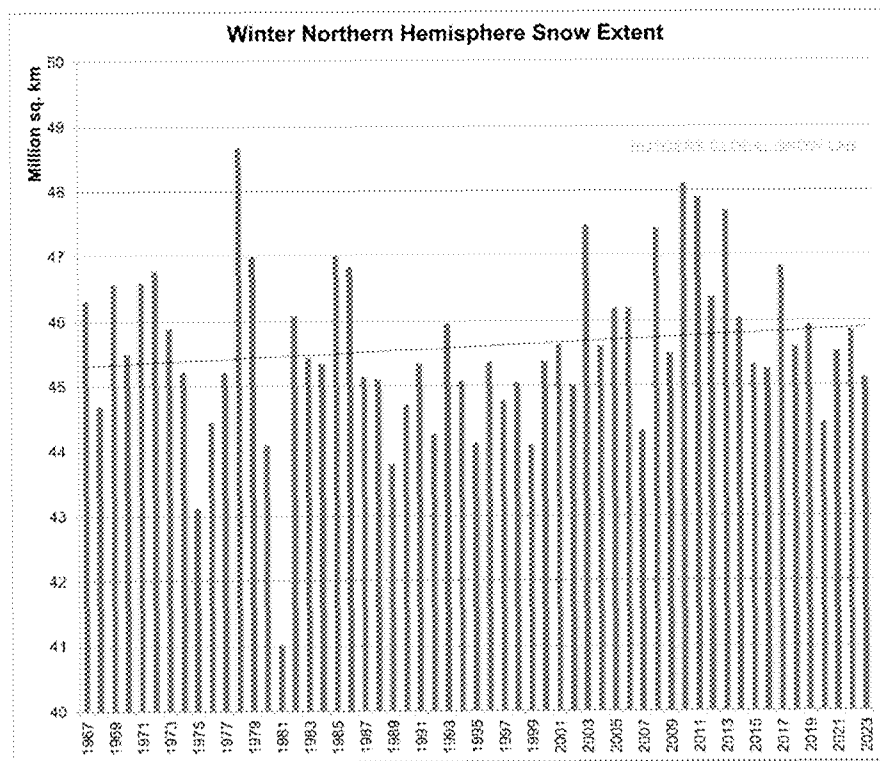


Figure 5.8: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (February 24, 2024)

Yet models project declining Northern Hemisphere snow cover due to climate warming, as described by Connolly et al. (2019).

The **climate models were found to poorly explain the observed trends** [in Northern Hemisphere snow cover]. **While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions.** Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant. Connolly et al. (2019).

CHECK IPCC ASSESSMENT

5.8 Hemispheric albedo differences

Intro text

That can be seen in [Figure 5.9 \[source at link\]](#), which shows the differences between the sunlight absorbed by the Northern and Southern hemispheres for the CMIP6 models. It is disturbing that the range is so large compared both to the observed value and to current human influences (about 2.5 Wm^{-2}).

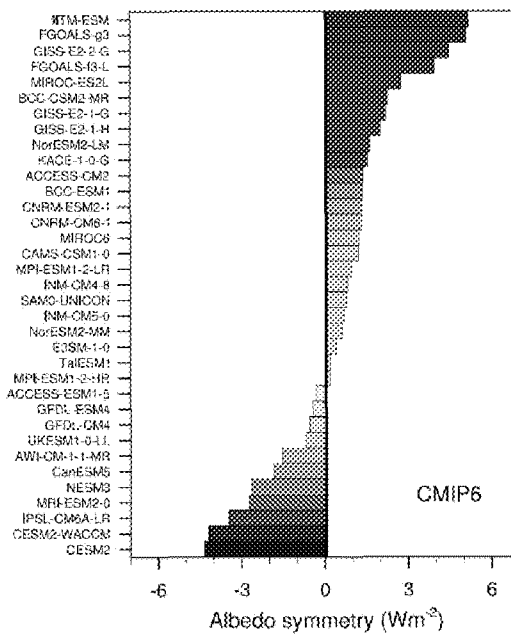


Figure 5.9: Differences in the reflectivity (albedo) between the Northern and Southern Hemispheres for members of the model ensemble used in the most recent IPCC assessment. The vertical black line shows the observed value and the colored bar shows the values generated within models. The very small observed difference is indicated by the vertical black line.

5.9 US Corn Belt

One of the largest discrepancies between models and observations is in the U.S. Corn Belt, a region of particular importance to global food production. Figure 5.10 shows the warming trends for summertime (June, July, August) for the 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) warm far too rapidly compared to observations (blue).

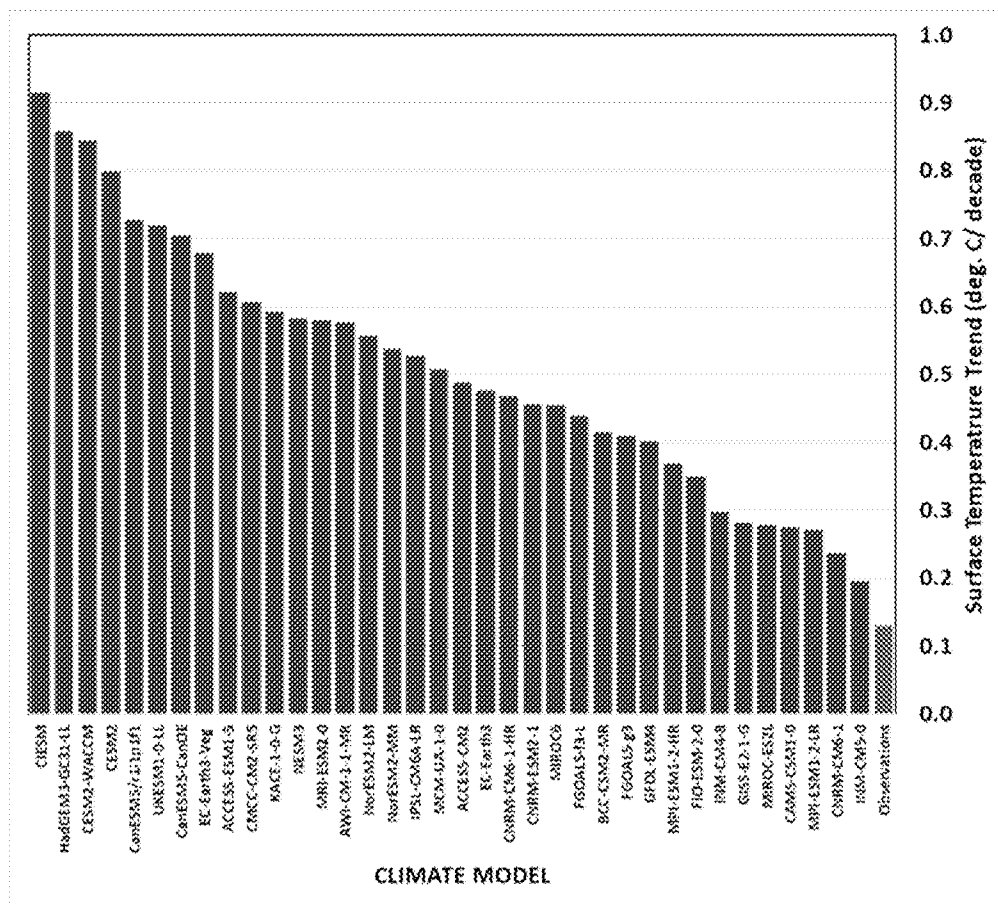


Figure 5.10: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases may be sufficiently large that the models are simply not fit for purpose.

As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from smallscale processes, we believe that **the current generation of models is not fit for purpose.** - T. Palmer and B. Stevens, PNAS (2019) [source at link]

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.

- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the corn belt.
- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in Watts/m² is three times larger than the direct anthropogenic forcing of CO₂.
- The IPCC has acknowledged some of these issues but not others.

2 CO₂ fertilization and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1 CO₂ and global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

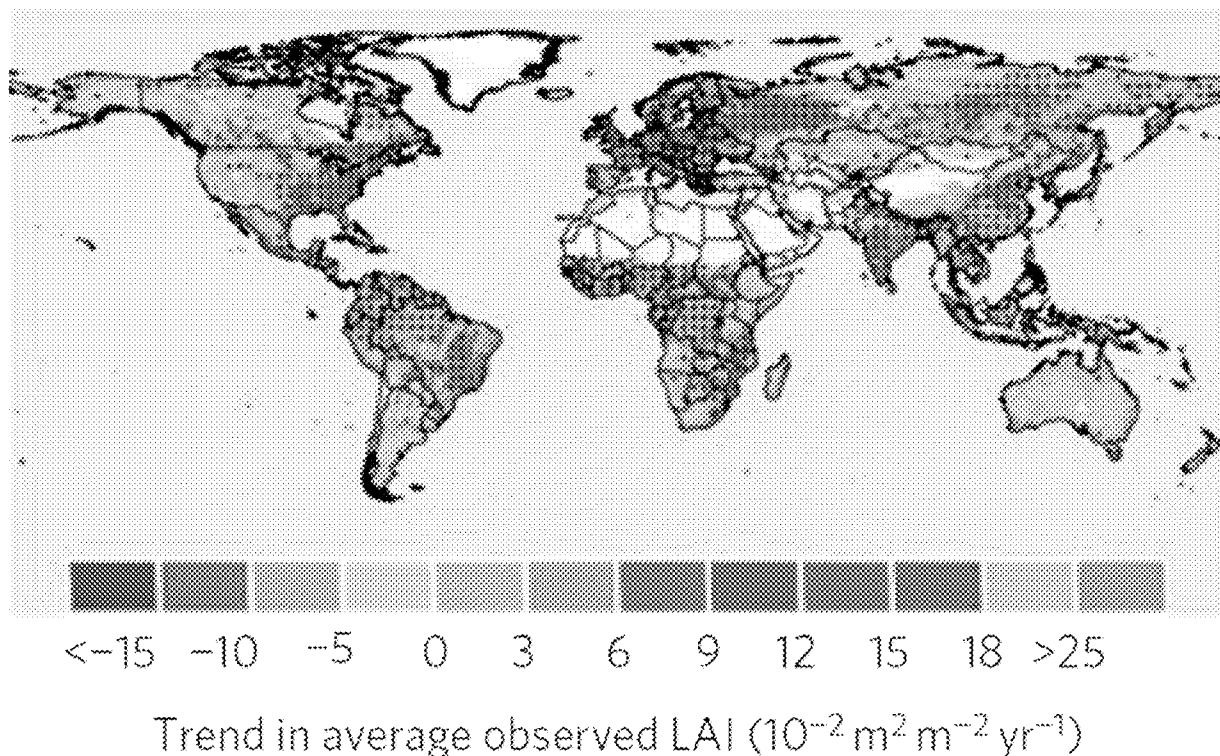


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.